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Essays on Efficiency and Growth of Ethiopian Air Transport Industry

Tsegay KALEAB

A dissertation submitted
to
The Department of Economics, Addis Ababa University

Presented in partial fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Economics

Addis Ababa University
Addis Ababa, Ethiopia
June 2020

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Approval sheet

This is to certify that the dissertation prepared by Tsegay Kaleab Atsbaha, entitled: ***Essay on Efficiency and Growth of Ethiopian Air Transport Industry*** and submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Economics complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Chair of Department or Graduate Program Coordinator

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The journey to complete this doctoral dissertation was full of pressure, ups and downs, and challenges and constraints but was possible for me to overcome all these thanks to enormous support from so many people. Without their involvement in one or another, this work would not have been completed.

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I am most grateful to my wonderful family whose love and guidance are with me in whatever I pursue. Most importantly, I wish to thank my loving and supportive wife W/ro Hilna Tewoldebirhan for her love and patience, being an amazing mother to our handsome boys Zoskales, Rodas, and our daughter Eminet Tsegay who brings so much joy into our lives. Thank you for all the love and support. I owe a great deal of gratitude to my beloved father priest Kaleab Atsbaha and my mother Letebrehane Sibhat, for their commitment to teaching me good behavior, sending me to school, and showing me the road to success. I also owe profound gratitude to my brothers and sisters for their constant moral support throughout my study. On behalf of all my brothers and sister allow me to thank Zerabruk Kaleab who is my right hand and *Thank you all!!!*

Tsegay Kaleab Atsbaha
Addis Ababa,

Ethiopia June 2020

Preface

This dissertation is submitted for the degree of Doctor of Philosophy at the University of Addis Ababa. This research was conducted under the supervision of Professor Almas Heshmati, main supervisor and Professor Tassew Weldehanna, co-supervisor in the Department of Economics between 2015 and 2020.

The dissertation follows an article-based approach. It is organized into five chapters. The first chapter outlines the common theme in all the four chapters. It justifies the need for efficiency and air transport growth research in the aviation industry in Ethiopia. It outlines the data sources for the research that follows in subsequent chapters. It discusses efficiency analysis literature in brief and how this can be applied to air transport. Each of the chapters that follow are original research work. They outline the key contributions of the dissertation by way of four original research studies included in the dissertation. Policy recommendations, limitations, and direction for future research are also included.

An overview of the status of the aviation industry in Ethiopia is also included in the first chapter. This covers the status of airports, air traffic trends, growth trends in aircraft types and numbers, and financial status of Ethiopian. Moreover, it also discusses trends in national, continental, and international air travel networks in the first chapter. Finally, this chapter provides a summary of all the papers.

The remaining four chapters (1 up to 4) are original single authored papers written following the format of a journal article. They start with an introduction where a background to the research problem is given. The chapters also discuss the rationale for studying the particular research problem and what contributions it makes. The objectives of the papers are also discussed in the introduction sections. This is followed by a brief literature review. The next section discusses the methodology followed including identifying the strategies followed and the way common econometric problems are addressed. The results and discussion sections present the findings of data analyses systematically. The final sections give the conclusion and recommendations where the key findings of the research are summarized and recommendations made based on the findings. References to previous works cited are included at the end. The appendices give additional information.

To the best of my knowledge, all chapters included in this dissertation are original except where references are made to previous works. Even though I have significantly benefited from the work of previous scholars in the writing of this dissertation, all errors that remain are solely mine.

Tsegay Kaleab Atsbaha
June 01, 2020
Addis Ababa, Ethiopia

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List of Acronyms

ACI	Airports Council International
ADD	Addis Ababa Bole
ADF	Augmented Dickey-Fuller
ADPI	Airport Di Paris Ingineering
AfDB	African Development Bank
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag Model
ASCEND	Flight Global Consultancy
ASK	Available Seat per Kilometer
ATAG	Air Transport Action Group
ATCs	Air Traffic Control
AXCR	Average Exchange Rate
BAA	British Airport Authority’s
BC-95	Battese and Coelli (1995)
CES	Constant Elasticity of Substitution
CES	Constant Elasticity of Substitution
CFCFGH	Caudill and Ford, Caudill, Ford, and Gropper (1995), and Hadri
Cost	Real Total Cost Birr
CV	Coefficient of Variation
DEA	Data Envelopment Analysis
EA	Ethiopian Airports
EAE	Ethiopian Airports Enterprise
EAG	Ethiopian Airline Group
ECAA	Ethiopian Civil Aviation Authority
ECM	Error Correction Model
ETB	Ethiopian Birr
EU	European Union
FE	Fixed Effect
GDP	Gross Domestic Product
GDP	Gross Domestic Product

GLS	Generalized Least Squares
GTRE	Generalized True Random Effects
IATA	International Air Transport Association
ICAO	International Civil Aviation Authority
JEL	Journal of Economic Literature
KGMHLBC	Kumbhakar, Ghosh, and McGuckin, Huang and Liu Battese and Coelli
KH-1995	Kumbhakar and Heshmati (1995)
KLH-2014	Kumbhakar, Lien, and Hardaker (2014)
LR	Likelihood Ratio
LR	Long run
LSDV	Least Square Dummy Variable
MLE	Maximum Likelihood Estimation
MLE	Maximum Likelihood Estimator
MoF	Ministry of Finance
MoT	Ministry of Tourism
MoTI	Ministry of Trade and Industry
MREM	Mundlak Random Effects Model
NBE	National Bank of Ethiopia
OECD	Organization for Economic Cooperation
OLS	Ordinary Least Squares
OTE	Overall Technical Efficiency
PP	Phillips and Perron test
PPF	Production Possibility Frontier
PRK	Passenger Revenues per Kilometer
PTE	Persistent Technical Efficiency
RE	Random Effect
RTE	Residual Technical Efficiency
RTK	Revenue Tonne per Kilometer
RTR	Real Total Revenue
RWSE	Real Wages and Salary Expenses

SF	Stochastic Frontier
SFA	Stochastic Frontier Analysis
SR	Short run
SSA	Sub-Saharan Africa
SURE	Seemingly Unrelated Regression Estimation
TE	Technical Efficiency
TFE	True Fixed Effects
TFP	Total Factor Productivity
TRE	True Random Effects
TREM	True Random Effects Model
TWA	Trans World Airlines
UK	United Kingdom
USD	United States Dollar
VEC	Vector Error Correction
VRS	Variable returns to scale
WPCI	World Consumer Price Index
XER	Imports and Exports

Chapter One

Introduction to and Summary of PhD Thesis on "Efficiency and Growth of Ethiopian Air Transport Industry"

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Abstract

This dissertation consists of an introduction and four independent, though related, papers on the growth and performance determinants of Ethiopian air transport and the production efficiency, cost efficiency, and labor use efficiency of Ethiopian airports. This introduction highlights the concept of the dissertation and provides an overview of the aviation sector's performance including the rationale for the study and the contribution that the four papers make to existing literature on air transport. The four stand-alone studies in this dissertation use different model specifications and estimations for estimating and ranking the performance of the airports. The differences in the airports' performance are attributed to the objectives of the airports, data availability, and the structure and the model's underlying assumptions. The aim of the independent studies is being published in academic journals in the field.

The first paper uses a cost minimization or input oriented approach for analyzing the cost efficiency of Ethiopian airports using the panel data stochastic frontier approach. It uses the time-invariant fixed effects, time-variant true fixed effects, specifying and estimating the time variant and time invariant approaches in Kumbhakar et al. (2015) and Battese and Coelli's (1995) models. The empirical findings show international airports have higher passenger volumes and also have lower cost efficiency compared to domestic airports. In other words, maximum cost efficiency was found at airports with low levels of services and facilities as compared to airports with better services and advanced facilities. The findings also show that airports having better infrastructure and airport specific facilities and services will continue to be inefficient compared to

those having lower levels of facilities and services. Hence, Ethiopian airports should introduce cost saving approaches based on reliable traffic forecasts.

The second paper uses an output maximization or output oriented approach for analyzing the production efficiency of domestic and international Ethiopian airports using the stochastic frontier panel data approach for the period 2002-17. This study examines the technical efficiency of Ethiopian airports over time. It specifies Kumbhakar et al.'s (2014) maximum likelihood method for separating persistent time-invariant inefficiency and transitory time-varying inefficiency from unobservable individual effects. It also applies the fixed effects model and distance technical inefficiency using Battese and Coelli's (1995) approach for a comparison. The findings indicate that most Ethiopian airports have relatively low technical efficiency which is required for developing competitive strategies that can attract more air traffic volumes and generate higher revenues. Hence, classic customer handling, policy, and incentive schemes should be introduced to increase passenger demand. Private and low-cost carriers should be encouraged to operate using the airports' services.

The third paper uses a factor demand approach and focuses on Ethiopian airports' labor use efficiency by analyzing this using the panel data stochastic frontier input requirement function. It also specifies the Kumbhakar and Heshmati (1995) model and maximum likelihood estimation techniques of separating persistent time-invariant inefficiency and transitory time-varying inefficiency for estimating labor use efficiency of Ethiopian airports. The findings show that domestic airports are relatively better performing as compared to international airports. Similarly, most airports experience high persistent inefficiencies compared to transitory inefficiencies. This implies a need for taking lessons in the deployment of labor resources and introducing minimum labor requirement standards at all airports.

The final paper examines the growth determinants of the Ethiopian air transport sector by testing the variables' significance and the causality of the three separate but interdependent activity equations covering the period 1988-2018. Ethiopian Airlines' passenger growth determinants, other airlines' passenger growth determinants, and the determinants of air freight cargo growth. In this research, ordinary least squares, a seemingly unrelated regression estimation, and autoregressive distributed lag modelling approaches are applied to investigate the short-run and long-run causal

relationships between air transport growth and some selected macroeconomic variables. The major findings show that most variables are statistically significant both in the short-run and long-run. Similarly, their respective error correction models are also significant and negative as expected implying strong and significant causal relationships between the short-run and long-run models. The econometric results of some specific variables vary which is attributed to high dependency on imported goods and services, absence of alternative passenger air transport systems, and steadily growing aggregate demand for air transport. Hence, the government should pay due attention to stable macroeconomic growth and airlines should have long-run strategic planning for reducing the effects of any internal and external shocks to the economy.

Keywords: Ethiopian airlines; aviation industry; air transport; airports; efficiency; growth; labor use; Ethiopia

JEL Classification: L93; J01; O4; D24

1. Introduction

1.1 Background

This thesis studies the Ethiopian air transport sector's growth and the efficiency of Ethiopian Airlines (henceforth Ethiopian) and Ethiopian airports. The two were merged in 2017 to form the Ethiopian Airline Group (EAG). Air transport in Ethiopia has a long history starting in the early 1930s. First, the Ethiopian Civil Aviation Authority (ECAA) was founded in 1944 and airport services and infrastructure was handled by ECAA. Ethiopian was established in 1945 with six Dc-3/C-47 airplanes. It was after almost six decades that the Ethiopian Airports Enterprise was formally established as an independent legal entity on January 24, 2003 (ECAA, 2017; EAG, 2018).

The aviation industry is a crucial global air transport network involving airlines, airports, air navigation service providers, and manufacturers of aircraft and their components. The ultimate objective of the air transport industry is connecting to the global economy, providing millions of jobs, making the quality of life modern, and connecting people internationally (ATAG, 2018; Heshmati and Kim, 2016; Heshmati et al., 2018). The African air transport industry has also a key role in realizing sustainable growth and development in the countries. A report by the Africa Development Bank (2019) shows that expanding air services leads to improvements in the level of services and prices for consumers and the national economies on the continent (ADB, 2019; Goldstein, 2001).

Heshmati and Kim (2016) summarize that statistical evidence of airlines' passengers, goods and services have an interdependence between the airline industry and the economy (Heshmati and Kim, 2016; Heshmati et al., 2018). They underline referring to the work of Porter (1990) about the importance for lowering costs, providing higher quality, or product innovations which form the basis of companies' competitive advantages. Fu and Peoples (2018) explain the critical factors in airlines' success on international air transportation routes as the availability and efficiency of international airport operations. Such an efficient air transport service depends on two key interdependent factors -- airlines and airports operations (Bitzan and James, 2016; Fu and Peoples, 2018). Growth in air transport also matters for airlines and airports' efficient operations and their importance has been shown in literature on efficiency which has grown significantly in the past four decades in the context of worldwide air transport. In most developing countries, the level of growth in air transport and its efficiency varies depending on the country's economic state, the government's policy initiatives, regional cooperation, and economic stability.

Ethiopian is one of the most noteworthy and the biggest African corporate organizations in terms of capitalization, aircraft assets, and the number of destinations that it flies to. The airline's overall capital has increased and its fleet currently stands at 121 planes with well-equipped world class aircraft maintenance and repairing; it also has an international standard pilot and mechanical engineering training center. Besides, Ethiopian is the first African airline that invested in expanding and modernizing its fleet and took delivery of the Boeing 787 Dreamliner and the Boeing 757 freighter aircraft. It operates the latest wide body Airbus A350 XWB. Ethiopian flies to 104 international and 23 domestic destinations. These make it the largest airline on the continent in terms of routes and planes.

Further, EAG is among the few companies in Ethiopia that has managed to remain competitive in the international market. According to Bright and Habte (2015) the annual contribution of Ethiopian air transport services reached about US$2 billion of its the national economy in 2015. In 2017-18 this figure stood at $3.1 billion in revenue and $245 million in operating profits. In the 2018-19 budget year EAG generated a total revenue of $4.2 billion. In addition, 10.6 million passengers and 432,000 tons of freight cargo were transported in 2017 (EAG, 2018).

In recent times. Ethiopian has further diversified its revenue sources within the group offering training to foreigners in its aviation academy and providing catering services to the airline and other airlines, and providing aircraft service and maintenance services to most African airlines. The total passengers (domestic and international) served by Ethiopian airports was estimated to be around 12.143 million during the 2018-19 fiscal year (EAG, 2019).

Heshmati and Kim (2016) add that economic theory divides efficiency into technical, allocative, and cost efficiency. A number of studies have reviewed (such as Colombi et al. 2014; Greene 2005a, 2005b; Kumbhakar and Lovell 2000; Kumbhakar and Heshmati 1995; Kumbhakar et al., 2014, 2015; Rashidghalam et al., 2016; Tsionas et al., 2015) analyzed the factors contributing to efficiency analyses of firms like airlines, airports, hospitals, industry, and agriculture. Methodologically, efficiency estimations are applied using parametric or non-parametric estimations depending on the data available and the objective of the study. In this dissertation panel data cost function, production function and labor use input requirement function are used. It also introduces the time series autoregressive distributed lag model (ARDL) approach for investigating the airline's growth.

The focus of this dissertation is on two inter-related wings of EAG - Ethiopian Airlines and Ethiopian airports which make up most of the air transport industry in Ethiopia. The one part of the study is on the growth determinants of Ethiopian while the other part is on an efficiency analysis of Ethiopian airports that is categorized or decomposed into production efficiency, cost efficiency, and labor use efficiency. Production, cost, and labor are among the important factors in the industry when it comes to taking decisions.

This introduction complements the main thesis. The dissertation addresses the current structure, capacity, and performance of the Ethiopian air transport system in terms of its service capacity, asset value, financial capacity, market share and provides some preliminary statistics.

The International Air Transport Association (IATA) reported that in 2015 and 2016 Africa's overall performance marked a loss of $900 million and $800 million respectively. Even though Kenya Airways and South Africa Airways are competitors of Ethiopian they faced many challenges and had to fight for their survival due to a combination of poor strategic management and a continent-wide lackluster approach in creating a favorable environment for African carriers (IATA, 2017). Ethiopian aspired to increase its share and a strategic partnership of the African aviation market. Accordingly, Ethiopian established its second passenger and cargo hubs in Lome-Togo in 2012 and 2013 respectively. Malawian Air in 2013 and Zambia Airways and Guinea Airlines 2018 entered into an agreement in 2018 and started operating with EAG having a 49 percent equity shareholding (EAG, 2019).[1]

[1] https://corporate.ethiopianairlines.com/AboutEthiopian/History

1.2 The rationale for the dissertation

Air transport is one of the driving forces of global economic growth and supporting sustainable development through employment, trade links, and tourism (ATAG, 2018). In the recent competitive environment because of globalization, air transport plays a significant role in eroding barriers between countries and catalyzing cross-border economic transactions. According to Heshmati and Kim (2016) and Peoples (2014) the airline industry is a principal actor as well as the main facilitator of the globalization process. Looking at EAG's success as an internationally competitive airline service provider that has managed to pull off a highly profitable conglomerate[2] makes it a case study worth exploring (Oqubay and Tesfachew, 2019). The fact that EAG hails from Africa and is also leads to more curiosity about understanding how this is possible, especially in view of the fact that it is a government owned and run business enterprise. Identifying the determinants of macroeconomic growth in the airline wing of EAG and exploring the possibilities of improving Ethiopian airports' technical efficiency (production, cost, and labor use efficiency) form the main rationale for this study.

Heshmati and Kim (2016) reviewed some recent literature on airlines and air transport and their findings showed that most studies were concentrated in the US and Europe while there were fewer studies in Asia which deserves attention. Africa and most developing countries have an extremely low coverage in literature, though the hostile environment for airlines that Africa provides is well known in the industry. Poor infrastructure, restrictive flying rights, and overpriced jet fuel make flying planes profitably trickier as compared to other parts of the world. Worst of all is the political meddling in the national carriers, most of which have succumbed to corruption, cronyism, and public-sector protectionism. The result is that most of Ethiopian's larger rivals—notably South African Airways, Kenya Airways, and Egypt Air -- are perennially running into losses and their survival is not because of their commercial viability but due to their governments' endless generosity. In a world of fat subsidies for national carriers, privately owned airlines have little chance of prospering (Abate, 2016; IATA, 2018).

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[2] EAG is an amalgam of Ethiopian Airlines (Domestic, Regional and International Passenger Airlines); Cargo Airline and Logistic Company; MRO Services; Aviation Academy; In-flight Catering Services; Airlines Hotel and Tourism Services; and Ethiopian Airports.

According to Bright and Habte (2015) Ethiopian's growth has been constrained by limited domestic capital, though many governments are financially supporting their major domestic airlines. Besides Ethiopia's financial sector lacks efficiency that limits even raising capital abroad. Above all, the Ethiopian economy is constrained by foreigners inhibiting financial service regulations and investment restrictions. The constraints and pressure is not of a sudden event rather has its long period perspective. EAG's (2018) capacity evaluation report cited was in the Economist in 1989 which praised Ethiopian for its "unqualified success", despite operating in a "disastrous economy" suffering from civil war, famine, and Marxist inefficiencies. Since then the airline has grown its yearly passenger numbers by over 1,600 percent. Ethiopian is now the envy of all African governments. However, the driving factor of Ethiopian air transport's growth and Ethiopian airports' efficiency and trends have not been well documented and researched.

The strategic approach in overcoming many challenges and obstacles and making a profit is a case worth a closer look. In addition to learning from the operations of the two important wings of EAG – Ethiopian Airlines and Ethiopian airports, it is also interesting to uncover and suggest possible ways of improving their future performance – efficiency and growth wise through a careful study.

Given the size and complexity of both its passenger and cargo operations, Ethiopian outperforms many other government-owned public enterprises in Ethiopia. Its performance can be regarded as respectable even when compared to private run businesses' operations. Hence, EAG's performance in general and that of Ethiopian airports in particular, begs the questions, "What are the growth determinants of Ethiopian air transport services?" and "How efficient is the Ethiopian Airports Enterprise and what factors drive its growth?"

EAG is competitive in Africa and has a respectable position in the global airport arena, but what is its relationship with the other macro variables? How does Ethiopian air transport respond to changes? Do airports perform as efficiently as they potentially can?

To address these overall questions, this thesis breaks down the growth determinants of Ethiopian and the efficiency of Ethiopian airports into three different efficiencies – production, cost, and labor use technical efficiency.

In particular, the thesis answers the following research questions:

- What are the growth determinants of Ethiopian air transport (determinants of Ethiopian, other airlines, and Ethiopian cargo)?
- What are the short-run and long-run relationships between the Ethiopian air transport sector (determinants of Ethiopian, other airlines, and Ethiopian cargo transport)?
- How can the direction of causality effect Ethiopian air transport's growth?
- How do the production inputs influence passenger and air freight output at Ethiopian airports/ major determinants of production outputs/?
- How do the major cost factors/determinants influence the cost levels and structures of airports?
- What are the determinant factors of labor use at Ethiopian airports?
- How efficient are Ethiopian airports in terms of passenger and cargo output?
- What does the overall cost and labor use efficiency of Ethiopian airports look like? How efficient are Ethiopian airports in terms of cost and labor use efficiency?
- What is level and trend of persistent and transitory production, cost, and labor use efficiency of Ethiopian airports?

1.3 Empirical issues and data sources

In keeping with an empirical study's demands this dissertation applies different econometric methodological approaches in the four papers. The econometric approach of this dissertation can be divided into two broad categories. The first three papers are based on a panel data approach of a stochastic frontier analysis (SFA) using national and sectoral data sources while the fourth paper uses the time series approach with secondary national macro-data sources. The methodological approaches and data used in the four papers are highlighted in this section.

1.3.1 Empirical efficiency analysis

Many literature reviews use a stochastic frontier analysis (SFA) and the data envelopment analysis (DEA) as applied to the air transport industry throughout the world in general. While some of the airport-specific studies focus on DEA which is a non-parametric approach, a few use the parametric SFA approach. Papers 1, 2, and 3 in this dissertation give the cost, production, and labor use efficiency analyses of Ethiopian airports using an advanced approach of a stochastic frontier panel data model. The empirical review of applying the frontier method to production, cost, and labor use efficiency frontier has been developed in the framework of production and cost theories. Aigner et al. (1977) and Meeusen and van den Broeck (1977) are pioneers in the stochastic frontiers efficiency analysis which they formulated independently as a frontier model that encompasses the random variable and inefficiency components.

The SFA production and cost models are extensions of the neoclassical model that differs from the others because of the existence of the inefficiency term (Aigner and Chu, 1968). The basic distinction between production and cost models is that the sign of the inefficiency term is negative in production inefficiency and positive in cost inefficiency models indicating lower output than the maximum that is possible and higher costs than the minimum feasible cost respectively. Labor use input is categorized as input minimization which is similar to the cost inefficiency assumption.

A. Cost efficiency

In the first paper on the cost efficiency analysis, four models are specified and estimated for analyzing the time-varying and time-invariant cost efficiency. The first model is the time-invariant fixed effects model but it is individual specific where the estimation is done without distributional assumptions and is similar (Schmidt and Sickles, 1984) to the standard fixed effects panel data model:

(1) $\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + yr_t + v_{it} + u_i$

Following Parmeter and Kumbhakar (2014) the standard fixed effects panel data model provides consistent estimates of (β) even though $\hat{\alpha}_i$ is a biased estimator of u_i since $u_i > 0$ by construction. In this model $\alpha_i = (\alpha_0 + / - u_i)$ are treated as fixed and unobserved individual firm effects that are applied for the cost and production function efficiency estimations respectively. As shown by Parmeter and Kumbhakar (2014) and Kumbhakar and Heshmati (1995), the fixed effects model is estimated using ordinary least squares (OLS) by including individual airport dummies to capture α_i which is called the least square dummy variable (LSDV), where the coefficients of the dummies are the estimates of α_i.

The cost efficiency analysis also uses Greene's (2005a) true fixed effects model as the second model for identifying the time-varying technical efficiency that separates inefficiency effects from unobserved individual heterogeneity effects. The basic difference lies in the treatment of α_i and its time-invariant assumption of inefficiency. Even though Greene's assumption of time-varying unobserved firm heterogeneity is criticized due to the existence of a firm's persistent inefficiency effect, short-run or transient technical efficiency is still viewed as an overwhelming concept.

The third model is based on Kumbhakar et al. (2014) and it separates both time-varying transitory technical inefficiency and time-invariant persistent technical inefficiency. The model developed by Kumbhakar et al. (2014) and Colombi et al. (2014) introduced a relatively better solution as compared to previous works. They embrace the structure of the four components along with the inherent weaknesses of the general panel data model. Given the inputs, in their model the error term is split into four components to take into account different factors affecting output. Kumbhakar et al. (2015) and Kumbhakar et al. (2017) explain the four components model as follows. The cost efficiency model follows Kumbhakar et al. (2014) and Colombi et al.'s (2014) model which is specified and provided as:

(2) $\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + \eta_i + u_{it} + \mu_i + v_{it}$

Hence, the two inefficiency components are $\eta_i > 0$ and $u_{it} > 0$ while μ_i and v_{it} are the other two components that are firm heterogeneity and random noise respectively.

In this model, a distinction between the persistent/time-invariant and transient/time-varying components of technical inefficiency is developed simultaneously from the same data as used by Colombi et al. (2014) and Kumbhakar et al. (2014). This proves that time-varying inefficiency is a short-run inefficiency of resource utilization and allocation. According to Colombi et al. (2014), Parmeter and Kumbhakar (2014), and Kumbhakar et al. (2015) and Kumbhakar et al. (2017) the underpinning concept is that time-invariant inefficiency is considered as persistent inefficiency which is part of the management style of individual firms and such inefficiency cannot be resolved without a change in the government’s policy for the industry (a change in firm-ownership and any other). Despite these facts, the residual component of inefficiency might change over time without any change in a firm’s operations (Kumbhakar et al., 2014).

The last model (fourth model) applied in the efficiency analysis is the technical inefficiency effects of Battese and Coelli’s (1995) model. The panel data is similar to the frontier cost/production function outlined earlier. The model assumes that u_{it} is independently distributed and its values are found by truncation at zero of the normal distribution, that is, mean $Z_{it}\delta$ and variance δ^2 or $N(Z_{it}\delta, \delta^2)$. The airport cost inefficiency function is specified as a time-variant technical inefficiency effect (u_{it}) in the stochastic frontier approach mentioned earlier where $\ln Z_{2t}$ is airport standard categories as per the International Civil Aviation Organization (ICAO). All these models have their own strengths and limitations.

To sum up, almost all studies are important and should be considered as a reference and use for comparison purposes. The true fixed effects model identifies time-varying transient technical efficiency of airports, the KLH-2014 model gives us a brief overview of time-invariant persistent technical efficiency and an overall mean average efficiency level of EAG’s Ethiopian Airports in general and of specific airports in particular.

B. Production efficiency

In the second paper, production efficiency of Ethiopian airports is analyzed using time-invariant fixed effects technical efficiency, KLH-2014, MLE, and inefficiency effects of BC-95 models. Except the maximum likelihood estimation approach, the other three models are similar to the models used in the cost efficiency analysis explained in the first paper. The estimation techniques and procedures of production in the time-invariant fixed effects approach, the Kumbhakar et al. (2015) model, and BC-95 inefficiency effects model are the same. They only differ in the microeconomic conceptual foundations of cost and production. The estimation approach for airports’ cost efficiency relies on the actual cost as compared to the potential possible minimum cost while airport output service production efficiency considers actual output against potential maximum output. Once the estimation results of the four models are compared to each other, their research importance depends on their underlying assumptions. In particular, among KLH-2014 and MLE models, MLE is more efficient in estimating technical efficiency.

The fourth model applied in the production efficiency analysis is the maximum likelihood estimation model. As compared to the KLH-2014 model, the maximum likelihood estimation approach generates higher estimated efficiency even though it is at the cost of having strong normality assumptions of the random error term (Filippini and Greene, 2016; Kumbhakar et al., 2017; Parmeter and Kumbhakar, 2014; Rashidghalam et al., 2016). Based on the time-invariant fixed effects model, the general formulation of the maximum likelihood function for the *ith* observation can be rewritten as:

$$\ln L_k = cons + \ln \Phi(\frac{\mu_{k^*}}{\sigma_*}) + \frac{1}{2}\left\{\frac{\sum_t \varepsilon_{it}^2}{\sigma_v^2} + \left(\frac{\mu}{\sigma_u}\right)^2 - \left(\frac{\mu_{i^*}}{\sigma_u}\right)^2\right\} - T\ln(\sigma_v) - \ln(\sigma_u) - \ln \Phi\left(\frac{\mu}{\sigma_u}\right)$$

(3)

where $\mu_{i^*} = \dfrac{\mu\sigma_v^2 + \sigma_u^2 \sum_t \varepsilon_{it}}{\sigma_v^2 + T\sigma_u^2}$ and $\sigma_* = \dfrac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + T\sigma_u^2}$

By summing $\ln L_i$ over i we can obtain the log-likelihood function of the model where, $i = 1,......, N$. Hence, the MLE of the unknown parameters is obtained by maximizing the log-likelihood function (Colombi et al., 2011; Filippini and Greene, 2016; Greene, 2008; Kumbhakar et al., 2013).

Once the parameter estimates and the error components are identified, further decomposition of the error term into four components and separating persistent and time-variant transitory inefficiency effects follow Kumbhakar et al.'s (2014 and 2015) multi-step estimation procedures. It is possible to consider the final estimated efficiency levels of Ethiopian airports with a greater focus on the MLE model.

C. Labor use efficiency

In the labor use efficiency analysis of Ethiopian airports, fixed effects model, Kumbhakar and Heshmati (1995) model, and the MLE model estimation techniques are used as estimation methodological approaches. Among these three models, a time-varying transient and time-invariant persistent technical efficiency of the labor use input requirement is identified using the KH-1995 and MLE models. In the fixed effects approach, only time-invarying labor use technical efficiency can be analyzed. Though the estimation techniques and procedures are explained in cost and production efficiency, this paper also highlights Kumbhakar and Heshmati's (1995) model estimation.

The labor use efficiency analysis follows Colombi et al. (2014) and Kumbhakar et al.'s models (2014) to separate time-invariant persistent labor use efficiency and time-varying transient labor use efficiency specified as:

$$(4) \quad \ln L_{it} = \alpha_0 + f(W_{rt}, Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + v_{it} + (u_i + \tau_{it})$$

where the error term ε_{it} is decomposed as $\varepsilon_{it} = v_{it} + u_{it}$. u_{it} is technical inefficiency and v_{it} is the statistical noise. The next procedure is separating the technical inefficiency into persistent (u_i) and (τ_{it}) residual components, that is, $u_{it} = u_i + \tau_{it}$. The first component is firm-specific while the second component is both firm- and time-specific. An estimation procedure under the fixed effects is a multi-step framework (Kumbhakar and Heshmati, 1995). Hence, the estimation results of the MLE model are considered as the final estimation results of labor use efficiency of Ethiopian airports during the study period.

1.3.2 An Empirical analysis of Air transport growth

The growth determinant of Ethiopian air transport (Paper 4) uses a time series analysis of OLS, SURE, and the autoregressive lag model (ARDL) estimation methods. The paper also specifies Ethiopian's passenger numbers, other airlines' passengers, and freight cargo growth as the dependent variables with some relevant variables for air transport being provided through the macroeconomic explanatory variables. To investigate the growth determinants and examining the long-run and short-run relationships including the direction of causality using the pairwise causality analysis, the paper uses the long-run ARDL, the dynamic short-run, and VEC models.

To estimate useful and meaningful results, stationarity testing is done using the Augmented Dickey-Fuller (1981) test to ensure the existence of a stationary series of a constant mean, constant variance, and constant autocovariances assumptions (Brooks, 2014; Enders, 2015; Greene, 2018). Similarly, in case of a structural break, the Phillips-Perron test (Phillips and Perron, 1988) was checked if a sufficient number of lags existed for capturing the data generating process. The results of ADF and PP tests specified the modelling framework through determining the number of lags to capture the data generating process and for fixing the level of integration for further advanced time series estimations. As a result, the popular ARDL approach developed by Pesaran and Shin (1995, 1998) and Pesaran et al. (1996, 2001) was selected and estimated.

Several studies (Endres, 2015; Greene, 2018; Kripfganz and Schneider, 2018; Narayan and Smyth, 2006) indicate that the general ARDL model is represented by the following equation:

$$(5)\quad Y_t = \gamma_{0i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \sum_{i=0}^{q} \beta_i X_{t-i} + \varepsilon_t$$

where Y_t' is a vector of the dependent variable and is a function in its lagged value and the variables in $(X_t')'$ are also current and lagged values of exogenous variables that are allowed to be purely I(0) or I(1) and cointegrating; β and δ are vectors' coefficients of the lagged endogenous variable and exogenous variables; γ is the intercept; $i = 1,....,k$; p, q are optimal lag orders of the dependent and regressors respectively; p, q may not necessarily have the same lag length; and ε_t is a vector of the random error terms with zero mean constant variance and are serially uncorrelated.

To analyze the long-run and short-run relationships among the variables under consideration, the bound cointegration test was done as a requirement for the ARDL approach as specified by Pesaran and Shin (1998), Pesaran et al. (2001) and Narayan and Smyth (2006). This test's results determined the existence of a relationship between both short-run (ARDL) and long-run (VEC) elasticities and estimated the short-run elasticities with the error correction that represents the ARDL model. By applying ARDL's VEC model version, the speed of adjustment to the equilibrium was also determined. To have a comprehensive understanding of the determinants of air transport's growth (Ethiopian, other airlines, and freight cargo), the causal relationship was also examined using the pairwise Granger causality test. This test assumes each variable as being dependent on its own VEC model equation (Narayan and Smyth, 2006; Ozkan and Karaman, 2011). Hence, the advanced times series methodological approach of the thesis gives a complete picture of both long-run and short-run relationships as well as their actual directions of causality.

1.3.3 Data sources

The first three papers use an annual panel dataset with similar data sources while the fourth papers use time series macro-data.

Data sources for Papers 1-3

In the first three papers 16 years' panel data was collected from 13 domestic and international airports.

The first paper focuses on an analysis of cost efficiency using the variables total cost, passenger output, freight cargo output, price of labor, price of energy, price of fixed assets, and price of long-run capital investments. The second paper does an analysis of production efficiency using the weighted sum of passenger and freight cargo, labor, maintenance, repairing and operating expenses, and real capital investments as the variables. The third paper analyses labor use efficiency by using the weighted sum of passenger and freight cargo outputs, average wage, energy consumption per productive labor hour, capital investment per productive labor hour, and maintenance and repairing per productive labor hour.

This research (production efficiency, cost efficiency, and labor use efficiency) used secondary sources for traffic, human resources, and financial data. The data is organized on a yearly basis. The data sources cover Ethiopian and Ethiopian airports while other selected macroeconomic variables were obtained from the databases of the Ministry of Finance (MoF) and the National Bank of Ethiopia (NBE).

The aggregated sum of the total number of annual passenger movements converted into weighted values in kilograms and annual air freight cargo transport are considered as cargo. One person along with his luggage is approximately equivalent to 100 kg of air freight cargo. Y1 is annual passenger movement in number and L is the man-day productive hours of each worker. The effective working hours are calculated by the actual number of workers multiplied by annual working hours excluding weekends and annual leave. The data provides information for specifying the stochastic frontier panel data models for 13 international and domestic airports. The data is obtained from annual records of Ethiopian Airports (EA). Based on a balanced panel data, 208 observations were made for the analysis covering the period 2002-17.

Measuring a workload unit is an aggregate of passengers with luggage who impose the same cost to the airport infrastructure with 100 kg of cargo. Mart ń and Voltes-Dorta (2011) state that such a weighted sum is more logical for airlines than airports since it directly effects the payload of aircraft and the same weight of passengers and freight may not require similar physical and financial inputs. The input variable of interest K is real net capital investment. This is the capital investment at an airport is used for the terminal's construction, runway construction, and apron and power house construction including large capacity generators and various capacity fire trucks. This capital investment is the foundation of an airport.

Paper 4's data sources

The fourth paper use time series data that covers the period 1988-2018. In this study Ethiopian air transport's growth determinants are explained as determinants of annual passenger growth and air freight cargo growth. Passenger growth is further divided into Ethiopian's passenger and other airlines' passenger growth determinants treated as the dependent variables. Ethiopian's average airfare (price per passenger), national per capita income, real gross domestic product, average exchange rate, world consumer price index, crude oil prices, and volume of imports and exports are explanatory variables covering the period 1988-2018.

The data used in this study comes from multiple sources. The per capita income (PCIM), world consumer price index (WPCI), average exchange rate (AXCR), volume of imports and exports (XER), and crude oil prices (Oil) are collected from the Ministry of Finance (MoF) of Ethiopia which in turn collects the data from different national account series; this is linked for harmonization with the National Bank of Ethiopia (NBE). The air passenger traffic (Ye) and freight cargo (Yo) data comes from Ethiopian Airlines Group's annual reports. Data on real GDP is obtained from MoF. Monetarily measured variables like nominal GDP are deflated by the GDP deflator (base year 2011). Population is obtained from various issues of the NBE database. Per capita income is calculated by dividing real GDP by the population. The other variables are collected from the Central Statistics Agency (CSA) of Ethiopia, the Ministry of Trade, and the Ministry of Tourism (MoT).

1.4 Contributions of this dissertation

The efficiency of the airline industry has been studied extensively. However, previous studies have been restricted to airports' operations in North America, Europe, and Asia. Little has been studied about airports on the African continent. This thesis contributes additional research inputs to the limited available literature on air transport in Ethiopia and Africa in measuring and identifying the efficiency and growth determinants of airlines and airports' growth. Thus, the results generated and the conclusions drawn are new to the aviation industry on the African continent.

The key contributions of this thesis include:

- This study is the first of its kind on the Ethiopian air transport industry.
- The thesis identifies bi-directional and unidirectional determinant factors of growth of the Ethiopian air transport industry.
- The research papers investigate the levels and trends of efficiency for Ethiopian and airports using various up-to-date model specifications and estimation methods.
- The findings on production, cost, and labor use efficiency can be used as initial scientific documents for short-term and long-term airport planning and operations and how they can be influenced positively through government policy inputs and regulations.

1.5 Policy recommendations

The following policy recommendations are made for the air transport industry and the government in general:

- According to the findings of this study, Ethiopian airports experience low levels of cost efficiency across airports and over time. The study also indicates that in the future as airport categories increase in the form of additional infrastructure, equipment and facilities, airports' cost inefficiency will increase. Hence, strategic airport leadership should introduce cost saving structural changes in the short-run and long-run as a matter of urgency. An analysis of labor use efficiency shows that deployment of resources above the minimum requirement should be reconsidered as a source of cost reduction. More importantly, a further assessment of operational as well as allocative efficiencies of all the airports is expected to address cost saving strategies and promoting cost efficiency.

- The findings of the production efficiency analysis show that despite huge airport capital investments, human resource deployment, and provision of services airports' output efficiency is low. This implies that the air transport sector in Ethiopia needs to develop competitive long-term and short-term strategies that can attract more air traffic customers. Policy and incentive schemes should be introduced to increase passenger demand. Support for infant private airline operators and low-cost carriers should be encouraged to effectively use the long hours when the huge capital infrastructure at airports is idle.
- The remarkable progress and achievements of Ethiopian should be appreciated and supported through sustainable national economic growth so that it can provide competitive passenger and air freight services globally. Structural changes should speed up the transition from an agrarian economic structure to industrialization in the country. Attention needs to be focused on policies oriented towards growing and expanding export oriented domestic industrial output, standardizing and improving the quality of products that can further assist in getting a trade balance and reduced dependency on world crude oil prices, the world consumer price index, and exchange rate volatilities.

1.6 **Limitations and guidelines for future research**

The limitations of this dissertation and future research options beyond what is offered by this dissertation are highlighted as:

a. The small sample problem of production, cost, and labor use efficiency analysis was due to data limitations. This made the sample sizes for the three studies small which limited the choice of alternative research methods. Even the available data could not be changed into quarterly data.

b. This dissertation addresses physical output production, various airport costs, and human and material resources but its findings are not inclusive. Further research should focus on the capital use, operational and financial/allocative efficiency of airports.

c. In addition to the determinants of aggregate air transport growth detailed behavior of the growth determinants, causes, and consequences of the price changes should be further contextualized.

d. Endogeneity issues have been considered in some recent papers. In this dissertation, Papers 1-3 do not deal with endogeneity separately with the assumption that a fixed effects procedure controls unobserved sources of endogeneity and the time trend in the fixed effects model further removes unobserved time effects. Hence, it is recommended to include this in future research.

2. Performance Overview of Ethiopian Airlines and Airports

2.1 Status of Ethiopian Airports

The Ethiopian Airlines Group is administering 23 airports. Among these four are international airport categories 9 and 6. Fourteen airports are airport category 5 and the remaining five airports are category 4. Airport category is given by the International Civil Aviation Authority (ICAO) based on the standard of equipment, facilities, and capacity depending on the aircraft fleet size and number and passenger services provided by an airport during peak hours (see Annexure A4). Crucial facilities and services include the number of runways, taxi ways, and apron stand size, fire bridge capacity and numbers, terminal capacity, contact gates, and remote gates. The highest airport stand is at the Addis Ababa Bole airport where 100 wide and narrow body aircraft can be accommodated. Most other airports have extremely limited apron size which can stand 4-6 aircraft at a time.

Airports also vary in their runway capacity. For instance, all types of aircraft can land and take off (B-747, MD-11) at the Addis Ababa Bole International Airport. Other airports have maximum capacity as specified by their critical fleet sizes. The three international airports (Mekelle, Bahir Dar, and Dire Dawa) have runways for the B-767 aircraft while most of the remaining airports have runways for the B-737 aircraft and in a few Q-400 aircraft can land and take off (see Annexure A4). Addis Ababa Bole International Airport’s terminal capacity has been upgraded to about 22 million passengers per annum with peak hour capacity of 594 and 2,345 passengers in the domestic and international terminals respectively.

2.2 **Traffic Trends**

Traffic data for air transport is commonly explained by the passengers served and freight cargo transported. Moreover, traffic data such as revenue per passenger kilometer and available seats per kilometer are preferred for analyzing airlines' capacity and performance. As shown in Table 1, the percentage of revenue per passenger kilometer, on average, was approximately 70.00 percent (of the available seat) while capacity growth as manifested by the growth in available seats per kilometer was, on average, 17.30 percent which is almost similar to RPK per ASK's 17.13 percent growth rate. Finally, the revenue per passenger kilometer growth rate was 15.45 percent higher than the global growth rate of 5-6 percent.

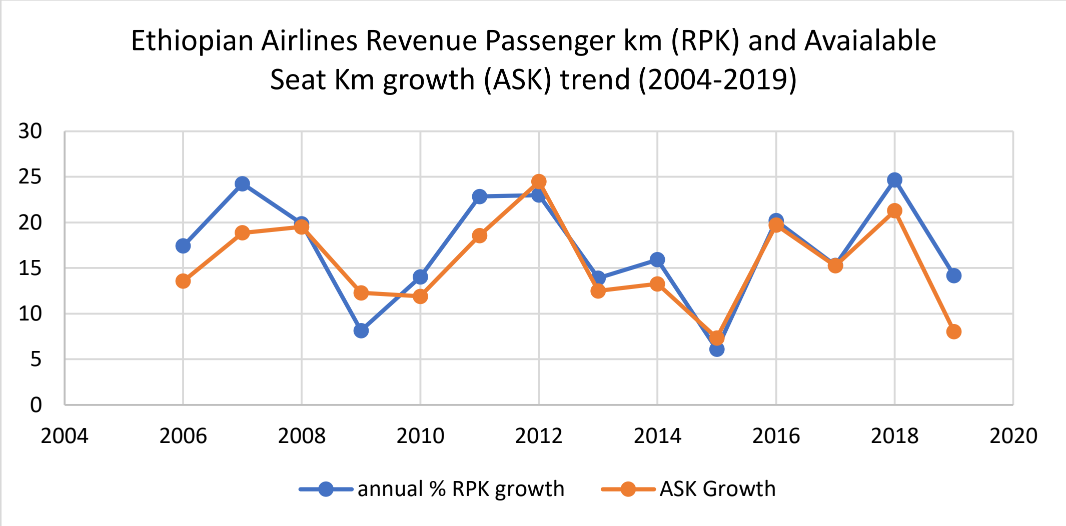
Table 1: Passenger revenues by kilometer and trends in available seat growth

Year	% Share of Revenue per passenger km (RPK) to ASK	Growth of Available Seats per km (ASK) %	Growth of RPK per ASK (%)	RPK Growth (%)
2006	64.00	17.42	21.70	13.58
2007	65.00	24.25	22.68	18.87
2008	70.00	19.87	10.64	19.52
2009	70.00	8.14	8.56	12.28
2010	72.00	14.02	10.68	11.90
2011	71.00	22.85	24.03	18.57
2012	72.00	22.99	21.74	24.47
2013	72.00	13.91	14.89	12.49
2014	71.00	15.92	17.26	13.28
2015	70.00	6.09	7.39	7.34
2016	68.00	20.19	23.18	19.72
2017	70.00	15.31	13.16	15.26
2018	74.00	24.67	17.50	21.28
2019	74.00	14.17	13.44	8.05
Ave.	70.00	17.30	17.13	15.45

Source: Author's calculations using the Ethiopian Airline Group annual report (2019).

Ethiopian's remarkable growth as shown in Annexure A3 doubled every five years (2005-18). For instance, the actual revenue per passenger kilometer in 2005 was 4.9 million while this number increased to 9.38 million in 2009. With an increase in passenger numbers, aircraft and other necessary facilities also expanded every year. Growth in the statistical data shows that the total annual revenue per passenger kilometer doubled every five years and reached 39.147 million in 2018. In other words, during the last ten years, Ethiopian air transport has expanded its capacity and performance more than four-fold which can be considered among the highest growth records in the history of world aviation.

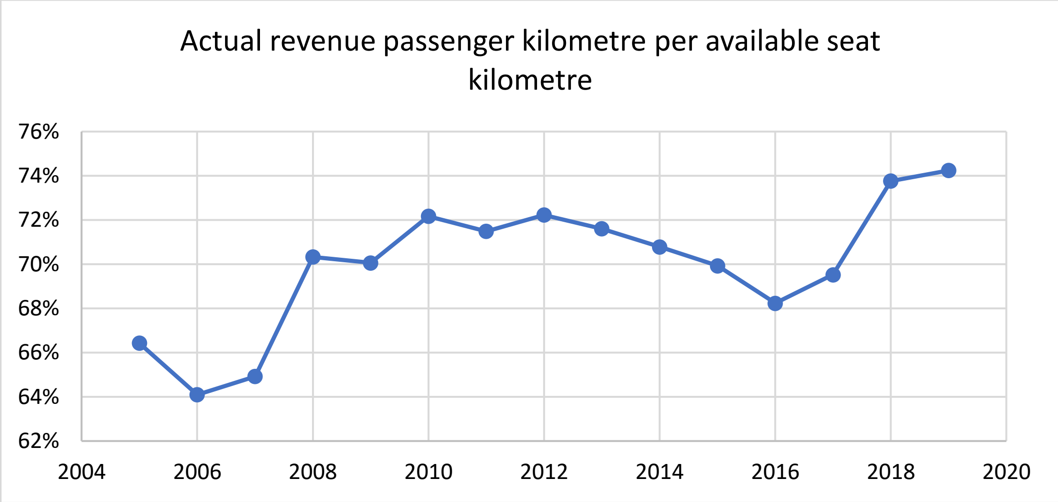
Figure 1: Comparison of revenue per passenger kilometer and growth in seats



Source: Author's calculations using the Ethiopian Airlines Group's annual report (2019).

The revenue per passenger kilometer as well as available seat per kilometer growth rate in Figure 1 shows 24.67 percent in 2018 maximum growth and lower growth rate revenue passenger per kilometer in 2015 at 6.09 percent. On the other hand, the annual available seat km growth rate showed a 24.47 percent in 2012 and 7.34 percent in 2015. On average, the annual revenue passenger growth was 15.45 percent during 2004-18. This is the highest in Africa and Ethiopian is categorized among the best growing airlines in the world. Taking a long-term historical perspective of the world air transport experience, the International Air Transport Association (IATA) and the Airports Council International (ACI) in their report on aviation benefits (TATA, 2019 and ACI, 2019) indicated that the growth in air traffic worldwide doubled every 15 years. The report underlined that air transport is experienced enough for achieving greater growth than most other industries throughout the world. Unlike most world air transport systems, the Ethiopian transport sector doubled its revenue, passengers, and passenger seats every five years. According to the Ethiopian Airlines Group its overall capacity in 2019 reached 60.2 billion available seats per kilometer.

Figure 2: Growth trends of revenue Passenger kilometer per available seats



Source: Author's calculation using Ethiopian Airlines Group's annual report (2019).

Of the available seats per kilometer, the performance of actual revenue per passenger kilometer grew every year ranging between 64 percent in 2006 and 74 percent in of 2018. As Figure 2 shows there was steady growth up to 2012 with some fluctuations but this declined in 2016 and then increased again in 2018. Overall revenue passenger trend showed healthy growth and detail total revenue per passenger kilometer and available seats is provided in annexure A3.

2.3 Growth Trends in Aircraft Types and Numbers

The capacity of an airline depends on its fleet size, the destinations covered, and market share. Table 2 shows aircraft types and size. It also shows the currently operating aircraft and ordered aircraft to show how the airline is using not only young aircraft and updated aircraft technologies too.

Table 2: Ethiopian's fleet matrix (types and numbers, actual and future status)

	Aircraft Type	Current	Future	Previous	Total
1	ATR 42/72	..	..	3	3
2	Airbus A350 XWB	14	1	..	15
3	Boeing 737	30	3	11	44
4	Boeing 757	..	..	12	12
5	Boeing 767	6	..	12	18
6	Boeing 777	20	..	..	20
7	Boeing 787 Dreamliner	25	1	..	26
8	De Havilland Canada DHC-8-400	26		1	27

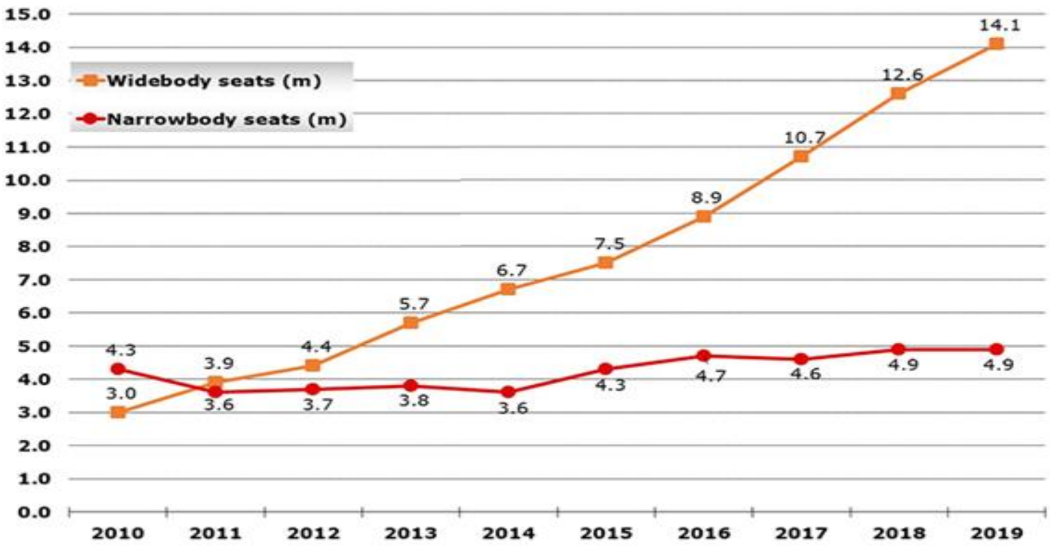
9	Fokker F50 / F60	..	..	5	5
10	McDonnell Douglas MD-11	..	..	3	3
	Total	121	5	47	173

Source: Author's calculation using Ethiopian Airlines Group's annual report (2019).[3]

Currently Ethiopian operates a young fleet of 121 aircraft flies to 125 destinations. Ethiopian's official website provides the actual and planned fleet status. The airline has 14 Airbus A350 XWB wide body aircraft, 81 Boeing aircraft, and the remaining 26 are De Havilland Canada DHC-8-400 aircraft which are usually used for domestic air transport (as of February 06,2020). In other words, about 95 wide body aircraft and 26 narrow body aircraft are actively serving passenger and cargo freight flights in the domestic and international air transport markets.

As reported by EAG (2019) Ethiopian has invested in expanding and modernizing its fleet. The average age of the Ethiopian aircraft is just 5.4 years which is young compared to 13.5 years for British Airways, 15 years for United Airlines, and 10.7 years for American Airlines. Ethiopian has the youngest fleet in Africa (Figure 3).[4]

Figure 3: Ethiopian's fleet size



Source: Extracted from Ethiopian Airlines Group's annual report (2010-19).

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[3] https://www.planespotters.net/airline/Ethiopian-Airlines,
[3] https://www.bbc.com/news/world-africa-47523958

Ethiopian commenced on December 30, 1945 while its flight operations started on April 08, 1946. The first historical international destination that Ethiopian flew to was Cairo on a weekly flight schedule from Addis Ababa. Ethiopian is a 74-year-old aviation company. Given these long years of service, it could have grown more. Compared to other African countries and Ethiopia's low level economic development, Ethiopian has successfully overcome social and economic instabilities and continues to grow. Unlike the improvements in the last 50 years, significant improvements have been observed in the past decade. Since 2011 the airline's focus has been on wide body aircraft as a part of increasing its market share and growth. As shown in Figure 3 the total number of wide body seats increased from 3.9 million to 14.1 million. On average, both narrow and wide body seats grew from 4.26 million in 2010 to 19 million seats in 2019 and approximately 12 million passengers were transported in 2019 which is a five-fold increase in less than a decade. Today Ethiopian is responsible for leading the Africa air transport sector and is playing a significant part in world air transport services (EAG, 2019).

2.4 **Brief Financial Status of Ethiopian**

Ethiopian continues succeeding and sustaining its growth in the aviation industry by generating revenue and making profits over decades. Table 3 shows that its growth has been improving with some fluctuations -- in 2016-17 the airline collected about 2.7 billion USD in revenue and achieved an operating profit of 232.8 million USD.

Table 3: Ethiopian's infrastructure value and financial status

Budget Year	Revenue in USD	Profit in USD	Infrastructure values in USD
2013/14	2,399,031,251	162,112,536	1,380,138,927
2014/15	2,418,121,516	172,661,302	2,017,683,129
2015/16	2,531,461,736	284,982,557	2,432,683,129
2016/17	2,713,445,732	232,817,309	7,745,183,129
Average	2,515,515,059	213,143,426	3,393,922,079

Source: Author's calculations using Ethiopian Airlines Group's factsheet (2018).

Though the airline market is challenging and volatile, Ethiopian has been making profits for years. Currently the basic infrastructure asset value of the company is about 7.745 billion USD and it is ranked among the largest airlines in Africa. On average, its operating revenue and profits were 2.5 billion and 213 million USD in four consecutive years. The underlying rationale for this sustainable profitable venture is EAG's operational efficiency.

2.5 **Trends in Worldwide Networks**

EAG is targeting 120 domestic and international destinations by 2025. Taking Addis Ababa Bole International Airport as the hub when this research was done, EAG connected with 103 international and 22 domestic destinations. Surprisingly, the Ethiopian's Vision 2025 has been achieved a head (before 2020). Hence, work on Vision 2035 is now about to start. With the intention of bringing the world close to Africa, Ethiopian is working hard to increase its worldwide network (routes). This shows that the airline's focus is shifting to having a successful future depending on first developing a far-reaching Pan-African route network. With this aim, new destinations and increased number of flights to Europe, the United States, Canada, Asia, and the Middle East have been launched. Ethiopian flies to a number of major cities in Europe including Frankfurt, London, Paris, Rome, Brussels, and Stockholm; to Bangkok, Beijing, New Delhi, Hong Kong, Guangzhou, and Mumbai across Asia; to numerous destinations in the Middle East; and to Washington DC, Los Angeles, Newark and Toronto in America.

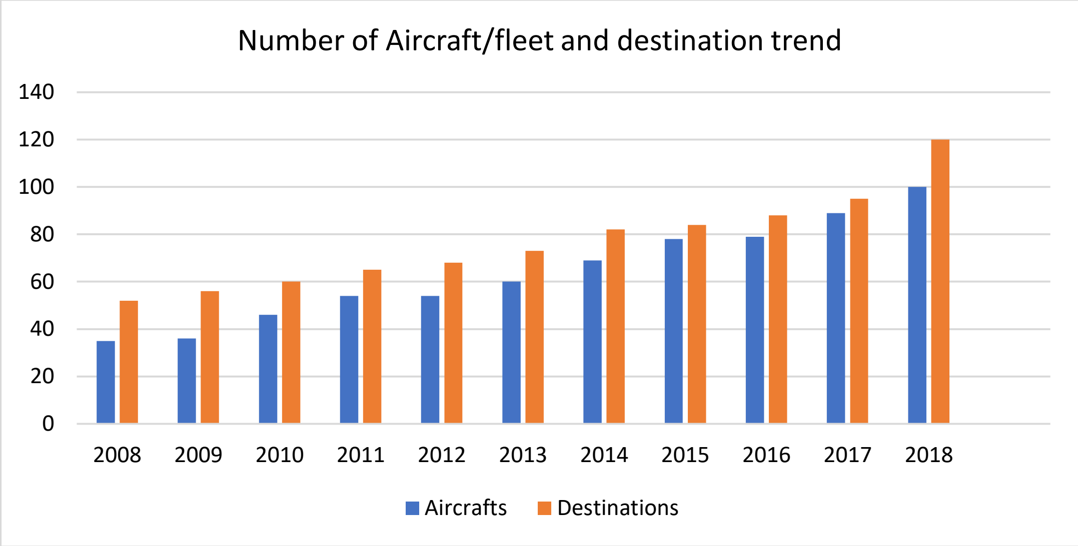
Table 4: Ethiopian's world destinations

No.	Continents	Countries	Destinations (airports)
1	Africa incl. Ethiopia	39	75
2	Middle East	8	11
3	Asia-Pacific	10	15
4	Europe	14	17
5	North America	2	6
6	South America	2	2
Total countries and destinations		75	125

Source: Author's calculations using Ethiopian Airlines Group's report (2019).

Direct international destinations (one-stops) and routings such as Addis Ababa through Harare and Lusaka are of key importance. Currently Ethiopian's network is broken down into 125 international and domestic destinations as shown in Table 4. The key reasons for these network routes include distance, market size, geographical location, and demand. Unlike the Eastern and Southern parts of Africa which have more frequencies and seats, Ethiopian has a small presence in North Africa (Algeria, Tunisia, and Morocco) and Western Africa (Sierra Leone, Liberia, and Mauritania). The most well-known African destinations are Nigeria (Abuja, Lagos, Kano, and port Harcourt), Nairobi, and Entebbe. As detail Ethiopian's route network is shown annexure A1 and an aircraft growth and destinations over time is also indicated in annexure A2.

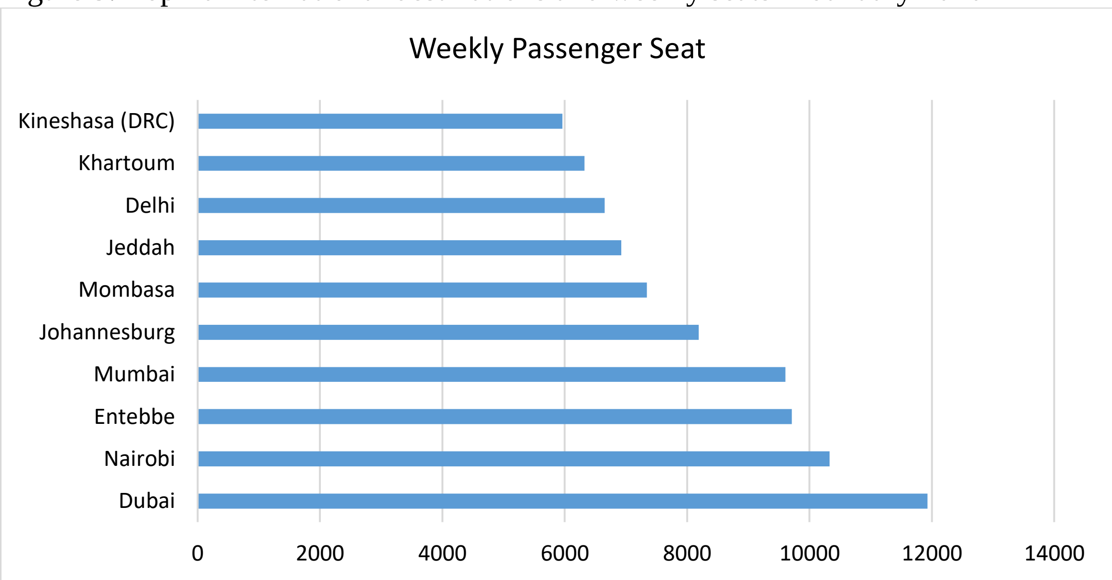
Figure 4: Trends in Ethiopian's aircraft numbers and destinations over time



Source: Author's calculations using Ethiopian Airlines Group's factsheet (2018).

Figure 4 shows the steady growth in Ethiopian's number of aircraft and destinations. It shows that in budget year 2007-08 it flew to 52 destinations throughout the world while its operational fleet had 35 aircraft. In the next five years (up to 2012), the fleet grew to 54 aircraft while the number of destinations increased to 68 airports. During 2013-18 the number of aircraft and destinations doubled to 100 aircraft and 120 destinations at the end of 2018. In 2019, Ethiopian served 125 destinations across 75 countries all over the world from Addis Ababa (see Table 4).

Figure 5: Top 10 international destinations and weekly seats in January 2020



Source: Author's calculations using Ethiopian Airlines Group's data (2020).

Many other destinations also have a large number of frequencies depending on market conditions. Figure 5 gives the top-10 destinations by the number of weekly total seats. Dubai leads this list with 11,926 available passenger seats. Ethiopia has thrice-daily flight services to Dubai, two of which are by wide body aircraft. Next is Nairobi with 10,328 available passenger seats and Entebbe with 9,710 passenger seats as of January 2020 every week. This implies that thousands of seats are available for transporting passengers. Worldwide Ethiopian market shares and coverage in terms of destinations is presented in Annexure 1. This study focuses on a descriptive analysis of Africa and China's market shares. Following Africa and China, Ethiopian's third and the fourth passenger destinations were Dubai and India respectively (EAG, 2019).

2.6 **Ethiopian's flights to China**

Ethiopian has been connecting Africa with China for a long period of time. Contemporarily the relationship in trade and foreign direct investments accelerated to its highest level in history. Due to this the air transport services to China are the strongest and have the largest market share for Ethiopian which operates regular passenger flights to all the five gateways in China (Beijing, Shanghai, Guangzhou, Chengdu, and Hong Kong and Pudong). EAG (2019) indicates that China is a leading country for Ethiopian in terms of total seats and an estimated 2.5 million passengers were transported between China and Africa in 2018.

Table 5: China-Africa traffic routes

Year	Passengers in million	Growth rate (%)
2015	2.08	0.00
2016	2.27	9.20
2017	2.38	4.80
2018	2.54	6.70

Source: Author's calculations using Ethiopian Airlines Group's annual report (2019).

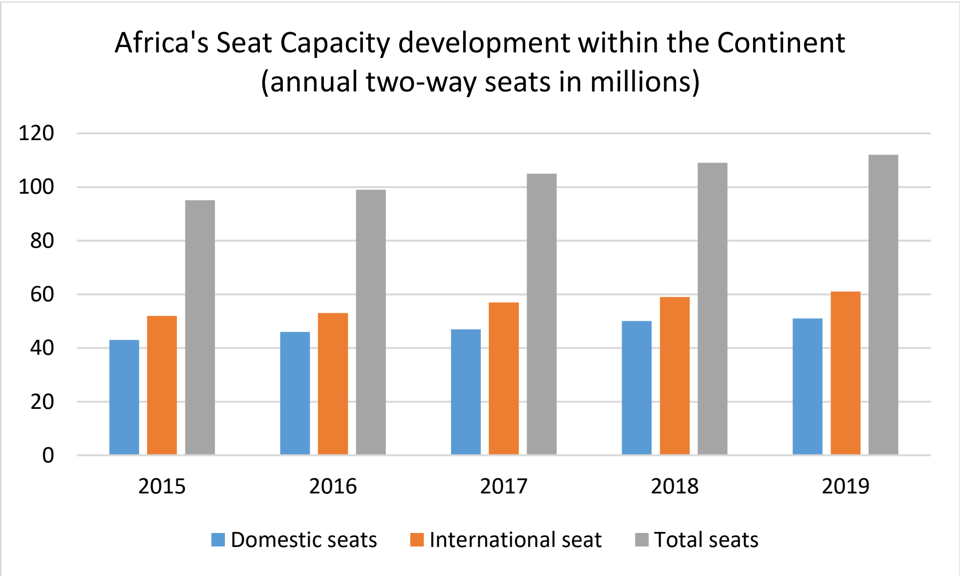
As shown in Table 5 Ethiopian transported about 2 million people between Africa and China in 2015. As business, investment, and tourism relations between the two increased, the airline also increased its capacity. The total number of passengers increased to 2.38 million and 2.54 million in 2017 and 2018 respectively with annual growth rates of 4.8 percent and 6.7 percent respectively. In other words, of the total passengers transported by Ethiopian, 10.6 million or about 24 percent were on routes that connected Africa with China in 2018 (EAG, 2018).

2.7 **Ethiopian's flights to African countries**

Ethiopian's largest market share is in the African market, followed by Dubai and Asia. The strong market network revolves around Africa and maximizing connectivity to the other world using Addis Ababa as its hub. Among the 10.6 million Ethiopian passengers more than 70 percent are transit passengers connecting between Africa and Asia-Pacific, Middle East, Europe, and South and North America.

EAG is implementing aggressive expansion into the African market. It thrived even during the global financial crisis and the oil crisis which were difficult times for most global airliners (EAG, 2018). Figure 6 gives Africa's seat capacity enhancement that demonstrate how Ethiopian continues to invest in African air transport growth.

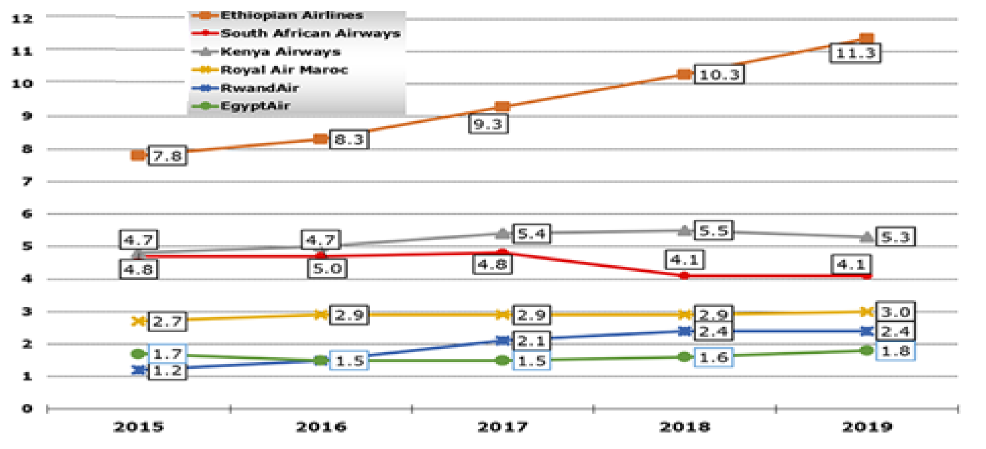
Figure 6: Development of two-way available seat capacity in Africa (as of January 2020)



Source: Extracted from EAG's annual report (2018-19).

Following the expansion of destinations and increase in flight frequencies in Africa, the number of available seats also grew. Including the Ethiopian domestic market, development of Africa's seat capacity is given in Figure 6. The domestic market's annual two-way seats increased from 52 million to 61 million between 2015 and 2019. Similarly, the international market within Africa increased from 43 million seats (2015) to 51 million seats (2019). Annual two-way seats (not per kilometer) for Ethiopian's domestic and international flights were 95 million in 2015, by the end of 2019 this number had increased to 112 million. Hence, seats in Africa have shown a progressive capacity increase in the past five consecutive years.

Figure 7: Capacity of the top-six African airlines (as of January 2020)



Source: Extracted from EAG's annual report (2018-19).

As can be seen in Figure 7, Ethiopian by far offers the highest number of passenger seats among the top six African airlines. This shows that Ethiopian had a lion's share of Africa's air transport market. Kenya Airways was the second top African airline while South Africa Airways was ranked third during 2015-19. The last top-six airline in Africa was Egypt Air. Many African airlines can learn some lessons from Ethiopian's growth experience.

In terms of total passengers, the South Africa O.R. Tambo International Airport served about 21.1 million passengers, the Egypt- Cairo International Airport was second with 15.9 million passengers, South Africa Cape Town International Airport was third with approximately 10.69 million, and Ethiopia's Addis Ababa handled about 10.6 million passengers in 2017/18. Though the air transport services in South Africa and Egypt are much bigger in terms of the passengers transported, compared to the capacity of all African airlines, Ethiopian is still the leader. This implies that there are other airlines that are operating air transport services with various degrees of capacity and experience.

3. Summary of each paper

This thesis explores efficiency and growth determinants of EAG's operations. It explores different aspects of its technical efficiency – cost, production, and labor use efficiency. Each of the papers is dedicated to one of these aspects of efficiency. I now present a summary of the four papers. The summary includes the title, objectives, methodologies used, key findings, and major takeaways from each paper.

Paper 1: An Analysis of the Cost Efficiency of Ethiopian Airports

This paper focuses on a cost efficiency analysis of 13 Ethiopian airports covering the period 2002-17 using the stochastic frontier panel data approach. The paper specifies the Cobb-Douglas cost function where cost is explained as a function of passenger output, freight cargo transported, and factor prices of labor, energy, fixed assets and capital investments. It specifies five models using both time-invariant and time-variant efficiencies. Besides, it also identifies persistent and transient efficiencies. The cost implications and efficiency effects of each airport show that time-invariant /persistent or low long-run efficiency exists with minor differences between the models while the short-run residual/transient efficiency levels have significant variations in the models.

The airports' efficiency levels indicate that all international service providing airports have lower cost efficiency compared to domestic service providing airports. The biggest hub, the Addis Ababa Bole International Airport is the least efficient while the Gode Domestic Airport is the most efficient. This implies that airports which have minimum services and facilities or infrastructure score better in terms of efficiency in both the short-run and the long-run. The study also finds that in the long-run, the biggest Ethiopian airports will continue to be less cost efficient compared to smaller airports. On the other hand, airports having better infrastructure, facilities, and services will continue to be inefficient compared to those having poorer infrastructure, facilities, and services implying that the size of the infrastructure is larger than the efficiency scale. Though the short-run efficiency is higher compared to long-run efficiency, Ethiopian airports should improve their efficiency levels both in the short term and develop long term efficiency improvement strategies in both aeronautical and non-aeronautical areas and explore the application of more cost saving strategies. More importantly, terminal and apron operations are expected to promote cost efficiency.

To sum up, Ethiopian airports have low levels of cost efficiency over time implying the need for developing standard infrastructure and also making provisions for expenditure. This also calls for an expenditure analysis in terms of a cost benefit analysis for reducing costs beyond production capacity. Similarly, expenditure and investments need to consider passenger and freight cargo trends more than social and political equity goals and objectives. The overall estimate of positive cost inefficiency implies that Ethiopian airports are experiencing high and increasing cost inefficiency in an increasing number of airport categories. An airport having a higher level of infrastructure, facilities, and special airport systems is associated with higher and increasing cost inefficiencies. Unless structural changes are made for cost savings the positive cost inefficiency effect will continue increasing and might lead to total airport cost inefficiencies. Hence, strategic airport leadership for structural changes at the airports, revenue generation, and cost reduction are urgently recommended.

Paper 2: An Analysis of the Production Efficiency of Ethiopian Airports

This paper analyses the production efficiency of 13 domestic and international Ethiopian airports. It estimates the Cobb-Douglas production function following a panel data approach covering the period 2002-17. In estimating the production efficiency, the focus is on the maximum attainable output that can be produced with the available inputs and technology following an output oriented approach. The level of efficiency can be measured using the ratio of actual output to maximum attainable output. Annual weighted average passengers served and freight cargo handled by each airport is treated as the dependent variable while labor, maintenance, repairing and operating expenses, and real capital investments are treated as explanatory variables. Both time-invariant and time-variant panel data stochastic production frontiers are estimated. The production model is estimated using several stochastic frontier approaches including the efficiency effects of the Battese and Coelli (1995) distance function, Kumbhakar et al. (2014), and true fixed effects (Greene, 2005) models. The models assume different underlying distributional assumptions and are estimated using the maximum likelihood method. The time-variant efficiency results differ across models. What is surprising about the findings is that many airports had very low levels of efficiency implying underutilization of the invested capital on infrastructure. Besides, since persistent or long-run efficiency of the airports is very low, the problem of inefficiency will stay for a long period of time unless urgent measures are taken and implemented by the government for bringing in structural policy changes. The negative and highly significant sign for the efficiency of an airport category implies that the technical inefficiency effect will reduce significantly as the categories improve for all airports.

Paper 3: Labor Use Efficiency of Ethiopian Airports

This paper focuses on the labor use efficiency of Ethiopian airports using an input requirement function approach. The study uses panel data for 13 international and domestic airports covering the period 2002-17. The variables used are productive labor hours as the dependent variable, and work load unit of passengers and freight cargo transported as outputs, average wage, capital intensity per labor hour, energy consumption per labor hour and maintenance and repairing expense per labor hour as the independent variables. Fixed effects, the alternative multi-step model's and maximum likelihood estimation (MLE) techniques are used for estimating airports' labor use efficiency. The work load unit of passenger and freight cargo outputs, energy consumption per productive labor hour, and annual time trend are identified as important determinants of labor use efficiency. Except average wage all the determinant variables per productive labor hour are statistically significant in both the maximum likelihood estimation and alternatives multi-step approaches. Technical efficiency is decomposed into time invariant persistent and time varying residual components. The labor use time-invariant technical efficiency from the fixed effects estimation results is estimated to be about 47.52 percent on average during the study period. The maximum likelihood and the alternative multi-step model's results show that the time-varying residual efficiency was on average 99.90 percent and 99.86 percent for both model while the time-invariant persistent efficiency was 49.65 percent and 50.67 percent respectively. The overall efficiencies were 49.60 percent and 50.59 percent respectively. Despite the minor differences in the estimation, many domestic airports were performing relatively better than the international airports. Thus, deployment of resources above the minimum requirements should be reconsidered as a source of cost reduction. Besides this, airports that have higher persistent inefficiency will continue to remain inefficient which may necessitate structural changes and a revision of employment and the labor use policy for increasing labor productivity.

Paper 4: Growth Determinants of Ethiopian Air Transport

This constitutes the fourth and final paper of the dissertation. It studies the growth determinants of Ethiopian air transport using the ARDL approach. This study investigates the short-run and long-run growth determinants of Ethiopian air transport using time series data covering the period 1988-2018. The air transport model is estimated using the autoregressive distributed lag (ARDL) and vector error correction (ECM) models. Its aim is explaining the variations in Ethiopian and other airlines' annual passenger air traffic and air freight cargo. The determinants of air transport growth include average airfares/price per passenger, national per capita income, real gross domestic product, average exchange rate, the world consumer price index, crude oil prices, and the volume of imports and exports. The national per capital income has positive and significant short-run and long-run effects showing a strong causal relationship with other airlines' passenger growth. In the case of Ethiopian's passenger growth, per capita income only has a long-run positive and significant causal effect. Most other results of the growth determinants of Ethiopian's passengers, other airlines' passengers, and air freight cargo have expected effects. The model shows that a large share of the disequilibrium from the previous year's shock converges back to the long-run equilibrium in the current year. Such a significant ECM shows the existence of a stable long-run relationship between per capita income and Ethiopian passengers. Besides, the major findings also show that most variables are significant in both the short-run and long-run and their respective ECMs are also significant and as expected. This implies that, in general, there exists a strong causal relationship among the dependent variables and their respective explanatory variables. The ever increasing macroeconomic variables and heavy dependency on imported goods and services, no close substitute for passenger air transport and growing aggregate demand for Ethiopian air transport services resulted in unexpected signs for some variables. Finally, Ethiopian should give due consideration in its vision development to the continuous changes in the macroeconomic variables.

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Annexure A:

Annexure A1. Ethiopian's route network

1	Europe (17)	Destination cities	Destination cities	Destination cities
		Brussels, Dublin, Frankfurt,	Stockholm, Vienna, Rome, Milan,	Madrid, Oslo, Paris,
		London, Manchester, Athens	Paris, Moscow, Marseille	Istanbul
2	North America (6)	Washington DC, New York	Chicago ORD, Houston	Canada, Las-Angeles (LAX)
3	South America (2)	Rio De Janeiro	Buenos Aires,	
4	Gulf and Middle East (11 cities)	Bahrain, Kuwait, Riyadh, Doha	Hong Kong, Jakarta, Jeddah	Tel Aviv, Dubai
5	Asia-Pacific (15 cities)	Beirut, Chengdu, Damma m, Bangkok, Beijing	Kuala Lumpur, Manila, Singapore,	Tokyo, Seoul, Shanghai
		Delhi, Guangzhou	Moscow, Mumbai, Muscat	
6	Africa 62 cities	Abidjan, Abuja, Accra, Antananarivo	Enugu, Gaborone, Goma, Harare, Luanda	Lubumbashi, Mbuji-Mayi, Malabo
		Asmara, Bamako, Blantyre,	Hargeisa, Khartoum, Kigali, Mombasa,	Lusaka, Maputo, N'Djamena,
		Brazzaville, Bujumbura, Comoros	Kilimanjaro, Johannesburg, Juba	Nairobi, Ndola, Niamey, Nosy
		Cairo, Cape Town Conakry, Cotonou	Kaduna, Kano, Kinshasa,	Be Ouagadougou, Pointe-Noire
		Dakar, Dar-Es-Salaam, Djibouti, Douala,	Kisangani, Libreville, Lilongwe	Seychelles, Victoria Falls, Windhoek, Yaoundé, Zanzibar
		Durban, Entebbe	Lagos, Lomé	
4	Domestic (23)	Addis Ababa	Dire Dawa,	Bahir Dar
		Mekelle		

Source: Ethiopian Airlines Group (2019) Ethiopian factsheet.

Annexure A2 Growth in aircraft and destinations over time

Year	Aircraft	Destinations
2008	35	52
2009	36	56
2010	46	60
2011	54	65
2012	54	68
2013	60	73
2014	69	82
2015	78	84
2016	79	88
2017	89	95
2018	100	120

Source: Author's calculations using data from Ethiopian Airports (2018).

Annexure A3 Total revenue per passenger kilometer and available seats

Year	Actual Revenue passenger km (RPK)	Available seats per kilometer (ASK)	% of RPK to ASK (LF)	RPK Growth (%)	Growth of ASK (%)	PAX Growt h (%)
2005	4,964,320,617	7,472,338,847	66	..	..	..
2006	5,829,261,464	9,093,694,042	64	17.42	21.70	13.58
2007	7,242,930,525	11,156,037,069	65	24.25	22.68	18.87
2008	8,681,919,295	12,343,345,252	70	19.87	10.64	19.52
2009	9,388,546,319	13,400,244,433	70	8.14	8.56	12.28
2010	10,704,817,374	14,831,555,262	72	14.02	10.68	11.90
2011	13,151,014,748	18,395,310,596	71	22.85	24.03	18.57
2012	16,175,046,000	22,393,783,000	72	22.99	21.74	24.47
2013	18,424,359,000	25,728,092,000	72	13.91	14.89	12.49
2014	21,357,774,000	30,169,529,000	71	15.92	17.26	13.28
2015	22,657,918,000	32,398,720,000	70	6.09	7.39	7.34
2016	27,233,138,000	39,910,011,000	68	20.19	23.18	19.72
2017	31,401,726,000	45,163,538,000	70	15.31	13.16	15.26
2018	39,147,196,000	53,067,290,000	74	24.67	17.50	21.28
2019	44,695,991,000	60,200,307,000	74	14.17	13.44	8.05
Mean	18,737,063,889	26,381,586,369	70	17.30%	17.13	15.45%

Source: Author's calculations using data from Ethiopian Airports (2019).

Annexure A4: Ethiopian Airports' basic and standards data

	Name of Airport	ICAO code	IATA code	Region	Airport Type	Airport Category	Runway Length (L*W)	Critical Aircraft	No of Aircrafts Stand
1	Addis Ababa Bole	HAAB	ADD	Addis Ababa	Int'l	9	3700*45m 3800m*60m	B-747, MD-11	100
2	Dire Dawa	HADR	DIR	Dire Dawa	Int'l	6	2700m*45m	B-767	5
3	Bahir Dar Ginbot 20	HABD	BJR	Amahara	Int'l	6	3700*45m	B-767	6
4	Mekele Alula Abanega	HAMK	MQX	Tigiray	Int'l	6	3700*45m	B-767	5
5	Gonder Atse Tewodros	HAGN	GDQ	Amahara	Dom.	5	2900*45	B- 737	4
6	Arbaminch	HAAM	AMH	SNNPR	Dom.	5	2800*45m	B- 737	4
7	Gode Dom.	HAGO	GDE	Somale	Dom.	5	2300*45m	B- 737	2
8	Jimma Abba Jifar	HAJM	JIM	Oromia	Dom.	5	2000*45m	B- 737	2
9	Jijiga Garad Wilwal	HAJJ	JIJ	Somale	Dom.	4	2500*45	B- 737	2
10	Gambella	HAGM	GMB	Gambella	Dom.	5	2500*45	B- 737	4
11	Asosa	HASO	ASO	Benishangul Gumuz	Dom.	4	2500*45	B- 737	2
12	Humera	HAHU	HUE	Tigiray	Dom.	4	3000*45	B-737	4
13	Axum Atse Yohanes 4th-	HAAX	AXU	Amahara	Dom.	5	2400*45	B-737	4
14	Lalibela Airport	HALL	LLI	Amahara	Dom.	5	2500*45m	B-737	4
15	Kombolcha	HADC	DSE	Amahara	Dom.	5	2500*45m	Q-400	2
16	Hawassa			SNNPR	Dom.	5	3000*45	B-777	2
17	Jinka			SNNPR	Dom.	5	2500*45	B-737	2
18	Dembidolo			Oromia	Dom.	4	2000*30	Q-400	2
19	Kebridar			Somali	Dom.	4	2400*30	Q-400	2
20	Nekemt			Oromia	Dom.	5	2500*45	B-737	2
21	Semera	HASM	ZSE	Afar	Dom.	5	2500*45	B-737	2
22	Robe/Goba	HAGB	GOB	Oromia	Dom.	5	2500*45	B-737	2
23	shire	HASI	SHC	Tigiray	Dom.	5	2500*45	B-737	2

Source: Author's calculations using data from Ethiopian Airports (2017).

Chapter Two – Paper 1

An Analysis of the Cost Efficiency of Ethiopian Airports

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Abstract

Cost efficiency is a key concern for any business. Existing efficiency analyses of airports mainly focus on minimizing costs maintaining the standards of the services provided. This chapter examines the cost efficiency of 13 Ethiopian airports during the period 2002-17 using the stochastic frontier panel data approach. It specifies the Cobb-Douglas cost function where cost is a function of passenger output, the freight cargo transported, and factor prices of labor, energy, fixed assets and capital investments. Its estimations are done using five models using both time-invariant and time-variant efficiencies. The two output cost elasticities is < 1 suggesting airport cost increases less than the output (increasing returns to scale). Airport cost was inelastic to change in passenger output and price of labour. The cost implications and efficiency effects of each airport provide evidence of time-invariant or low long-run persistent efficiency with minor differences between the models while short-run transient efficiency levels have significant variations between the models. Airports' efficiency levels show that all airports providing international services have lower cost efficiency compared to those airports which provide domestic services. The biggest hub Addis Ababa Bole International Airport is the least efficient and the Gode Domestic Airport is the most efficient. This shows that airports with minimum services and facilities or infrastructure score better in terms of efficiency. Though the short-run efficiency is a little high compared to long-run efficiency, overall the cost efficiency of the airports was low. Hence, government interventions for bringing structural changes in airports' cost saving strategies are crucial. Ethiopian airports should improve the cost efficiency levels in the short-term and develop long-term efficiency improvement strategies by using more cost saving approaches.

Keywords: cost efficiency; time-varying; time-invariant; persistent and transient efficiency; airports; Ethiopia

JEL Classification Codes: C12; C14; C13; C23; D24

1. Introduction

Worldwide the air transport industry has played a significant role in economic development and demand for this industry's services is very high and will continue to increase. A report by the global aviation industry High-level Group on aviation's benefits underlined that air transport is improving the lives and livelihoods of billions of people around the world (ICAO, 2019). Globally, the aviation industry acts as an economic engine for the world economy. Taking United Kingdom's economic size and population as an example, the Air Transport Association Group (2019) reported that the aviation industry's contribution (direct, indirect, induced, and catalytic) was approximately about $2.7 trillion to the country's gross domestic product (GDP), and it supported about 65.5 million jobs worldwide in 2017. The International Air Transport Association's (IATA, 2018) mid-year report showed a doubling in the networking airport-routes (city pairs), and passenger air transport costs reducing by half during the past 20 years. This encouraged passengers to spend about 1 percent of the world GDP on air transport. In 2017 airlines generated approximately $38.00 billion in profits signifying the airlines' contribution to economic development (IATA, 2018). Overall the provision of passenger services at airports and by airlines was fast and safety and security at the airports and in airlines made air transport one of the most preferred modes of transport. This is the reason why it is important to continue providing value for airlines and airport users in the value chain.

Even though air transport makes multidimensional contributions to the economy, the airline industry in particular is experiencing low levels of profitability (Heshmati and Kim, 2016). Airlines are operating under strong international market competition. Besides, it is a capital-intensive industry. Hence, it requires large capital investments (procurement of aircraft), high standard of facilities, and high-quality maintenance and operational equipment. Consequently, competition and the industry being capital intensive results in reduced revenues and high fixed costs. The nature of the aviation industry is highly volatile and extremely sensitive to losses and bankruptcies. Sustainability of the aviation market depends not only on a country's market capacity but also airlines' regional, continental, and world market shares. As airlines increase their market shares, the volume of passengers at airports (hubs) also increases. As additional passenger generates revenue and this in turn requires service provision with its associate cost for the aviation industry.

With the increasing interconnections in the world economy, sustaining economic growth and healthy economies depend on the efficiency of air transport (Peoples, 2014). Multinational companies have to look beyond their domestic markets when selling their goods and services as well as buying components for production at low costs but of high quality. As Peoples' (2014) indicates, international trade accounted for about 6 percent of global GDP, where global companies required efficient and reliable transportation. Bitzan and James (2016) explained about existing and future challenges for sustaining efficiency gains in the air transport sector. Consumers require uninterrupted high-quality services with continuous frequent departures. Airlines have to provide these and have to work at operating at low costs even though air transport is facing volatile fuel prices.

Ethiopia owns one of the most competitive aviation industries in Africa (EAG, 2017). However, it faces a number of challenges related to competition and price escalations (EAG, 2017). The existence of an unpredictable political situation in Africa such as in Somalia and South Sudan and growing competition from other operators, the imported capital-intensive nature of the business, and the growing price escalations are some of the risks associated with the aviation industry. The aviation industry in general and the Ethiopian aviation industry in particular are also experiencing a cost paradox as there is pressure to reduce airlines' costs due to the industry's competitive nature while in practice operating costs of the aviation industry are increasing. In addition, flight delays, inadequate airport facilities, weak customer handling, and baggage being lost are a few of the other problems that airline operators and passengers experience at many airports including at Ethiopian airports.

According to Ulku (2009) providing quality passenger services and decreasing average delay time are some of the concerns for airlines and passengers. These are core problems and have multidimensional implications. As Ulku (2009) explains, delay in an aircraft on the runway, for instance, negatively affects efficiency from two perspectives. As an immediate effect, this delay increases airlines/ passengers' costs in the network system for transit passengers. Another consequence is that repeated delays in flights reflect constraints in airport capacity and reliability of air traffic control

(ATCs) systems that have a significant role in decreasing passenger demand in the medium and long terms. The other dimension which is more serious is the level of services offered to airlines and passengers, other facilities provided, and many suppliers' functioning which are impacted by the delays. This includes passenger entry points, car drop off and car parking, security check points, services at the checking counters going up to the boarding gates, and arrival processes along with the overall luggage management process.

In addition, the quality of ground handling services plays an important role in the efficiency of airlines' and the performance of airports as well. Limitations in the quality of ground handling services significantly contributes to delays in flights in addition to air traffic congestion in the taxiway, apron, and runway systems in both departing and arriving airports. Each delay means additional operating expenditure and maintenance and repair costs for airports.

A question that arises here is how are airports responding to these challenges and concerns and how are they measuring their efficiency? Ethiopian airports have been designing and implementing various strategies for improving their performance (EAG, 2018). Efforts have also been made to expand important facilities as well as efficient and effective utilization of existing resources such as parking, passenger terminals, and ground handling services. A significant amount of resources such as capital and recurrent costs have also been allocated for supporting systems and facilities. However, despite all these efforts to mitigate losses, a lot more needs to be done to reduce airports' inefficiency levels. These challenges and concerns about airports' efficiency also continue unabated necessitating in-depth research or an efficiency analysis particularly based on the recent available data related to cost efficiency which is the core issue and the main interest of this research. Among the various alternative research methods, a panel approach using a stochastic frontier analysis (SFA) fits the best for a cost efficiency analysis in the service sector.

Literature on the panel data stochastic frontier (SF) analysis has significantly improved in terms of identifying efficiency as well as coverage of sectoral disciplines. A lot of research has been conducted in agriculture, manufacturing, airlines, airports, hospitals, and banking sectors. In most of these studies, time-invariant and time-varying models are applied. Many different panel data models are estimated using both time-invariant and time-variant SF models. For instance, Kumbhakar et al. (2014) analyzed six SF panel data models in their work on Norwegian grain farming, while Kumbhakar et al. (2015) estimated 12 panel data SF models applied to different disciplines, Karagiannis and Tzouvelekas (2009) estimated ten short-run SF models for Greek olive oil, and Alem (2018) did a study of agriculture cost efficiency based on a multi-input output framework for seven competitive SF panel data estimation models. Heshmati et al. (2019) estimated five panel data models for airlines' cost efficiency. They found that efficiency results were sensitive to the inefficiency model's specification. To the best of my knowledge, no other study has used the same dataset for an airport specific efficiency analysis. Besides, a study of SFA using up-to-date parametric approaches for airport-specific multi-input and multi-output approaches is limited or not covered by existing literature which motivated this study for filling this gap in literature.

As explained by Heshmati and Kim (2016) in economic theory there are three main types of efficiencies -- technical efficiency, allocative efficiency, and cost efficiency. Technical efficiency focuses on the effectiveness of a definite set of inputs used for producing output while allocative efficiency is a mix of selected inputs that produce a specific output at minimum costs. The third cost efficiency is interchangeably used with economic efficiency to bring in line both technical and allocative efficiencies. Since cost efficiency is the core of all economic analyses, this study mainly focuses on the cost efficiency of Ethiopian airports. Airports' main objective is minimizing the cost of producing services at a given level of output and input prices. Accordingly, an efficiency analysis of Ethiopian airports is done using the panel data stochastic cost frontier approach by applying the fixed effects time-invariant model and the maximum likelihood approaches to separate time-varying and time-invariant efficiencies such as the true fixed effects model (Kumbhakar et al., 2015) and the distance efficiency function model.

Ethiopia has several airports that provide national and international air transportation services. Since airports' efficiency is important for national economic growth. This study examined major cost determinants and estimates airports' efficiency and compares the national and international services provided in the country subject to same regulatory and environmental conditions. This study estimates the efficiency of 13 airports in Ethiopia for the period 2002-17. In this study, long-run or persistent time-invariant as well as short-run or transient time-varying inefficiency of Ethiopian airports' service provisions using a cost function approach is estimated. It identifies cost efficiency levels across airports and over time. The findings include the need for cost saving strategies as being urgent and recommends further research related to airports' operational and allocative cost efficiencies.

This rest of this chapter is organized as follows. This introduction covers issues related to trends in terms of opportunities and threats, motivation for the study, and the study's methodology. Section 2 gives a theoretical and empirical literature review of the stochastic frontier approach as well as previous studies on airports' performance. Section 3 describes the data. The model specifications are given in Section 4. Section 5 provides details of the model's estimation and a discussion and interpretation of the results while the final section gives the summary and conclusions.

2. Literature Review

2.1 Theoretical literature

The concept of a stochastic frontier model was first introduced five decades ago in economic literature. This sub-section reviews the use and development of stochastic frontier models assuming input oriented technical inefficiency as a cost frontier function. Aigner and Chu (1968) were the first to come up with the concept of a Cobb-Douglas stochastic frontier analysis. Accordingly, the stochastic cost frontier model can be specified as:

(1.1) $\ln C_i = x_i'\beta + \eta_i$

η_i is a positive random variable related to technical inefficiency. A decade later, Aigner et al. (1977) and Meeusen and van den Broeck (1977) independently formulated a frontier model that includes a random variable and inefficiency. The introduction of a random variable, commonly called statistical noise, helped bridge a gap in the earlier frontier model. The model can be re-written as the Cobb-Douglas cost frontier model as:

(1.2) $\ln C_i = x_i'\beta + v_i + \eta_i$

In this model, a specific distinction is made in representing the values of the terms η_i and v_i. Thus, the term η_i represents the inefficiency term as a gap from the minimum feasible cost (non-negative random error and half-normal distribution) and v_i is a symmetric random error which accounts for statistical noise and is considered as an exogenous variable or influencing cost beyond the control of the producer. It is normally distributed as $v_i \sim (0, \sigma_v^2)$. Since the output value of the model is bounded from above by the stochastic variable $\exp(x_i'\beta) + v_i$, we call it the stochastic frontier model. The value of the random error v_i can be positive or negative. This varies the value of the stochastic frontier as per the deterministic part of the model $\exp(x_i'\beta)$ and stochastically vary by v_i.

The stochastic frontier models considered the error term (ε_i) as a composite disturbance that can be decomposed as:

(1.3) $\varepsilon_i = v_i + \eta_i \quad i = 1,\ldots..,n$

Kuosmanen and Fosgerau (2009) and Parmeter and Kumbhakar (2014) explain that the appearance of these two distinct error terms in the stochastic frontier model made it different from the standard cost function. Full efficiency is an assumption of the standard neoclassical production/cost functions where the error term $\eta_i = 0$. Thus, the neoclassical production/cost function becomes a special case of the SF model. Even though the SF production/cost model is an extension of the neoclassical production/cost model, in a stochastic frontier analysis the existence of the inefficiency term can be examined using the hypothesis of variance of $\eta_i = 0$ or the inefficiency variance term. The production and cost function models differ by the sign of η_i which is negative and positive in production and cost models respectively implying that inefficiency lowers output (negative sign) than maximum output and higher costs (positive sign) than minimum cost, respectively.

Even though a model for the stochastic frontier function was developed, technical inefficiency was not estimated for some time. Jondrow et al. (1982), were the first to develop a method for estimating the technical inefficiency of a firm.

In the cost frontier function the objective is commonly set as producing a given level of output at minimum feasible costs (Kumbhakar and Parmeter, 2014; Heshmati, 2013). According to Kumbhakar and Parmeter (2014) the basic assumption is that a firm is technically inefficient, that is, either it is producing less than the maximum potential output level or utilizing excess inputs than the minimum required amount to produce the given level of output. Hence, technical efficiency or a firm having minimum costs is given by $\ln C_i^* = x_i'\beta + v_i$ while a technically inefficient firm assumes additional or actual observed costs by the amount of inefficiency, that is, $\ln C_i^a = x_i'\beta + v_i + \eta_i$. This can be rewritten as:

(1.4) $\ln C_i = \exp(x_i'\beta)\exp(v_i).\exp(\eta_i)$

where β is the deterministic parameter, $\exp(v_i)$ is the error noise, and $\exp(\eta_i)$ is the inefficiency value. The cost efficiency of a producer is measured as the ratio of minimum to actual costs as:

(1.5) $TE_i = \dfrac{C_i^*}{C_i^a} = \dfrac{\exp(x_i'\beta + v_i)}{\exp(x_i'\beta + v_i + \eta_i)} = \exp(-\eta_i)$

The value of the cost efficiency is between 0 and 1. It is a measure of the cost of the i-th firm relative to the minimum cost for producing a given level of output by a fully-efficient firm. An inverse of equation (1.5) is larger than 1. The part in excess of 1 is the percentage higher cost due to cost inefficiencies. The first step in predicting technical efficiency in Equation (1.2) is estimating the parameters of the stochastic production frontier (Kumbhakar and Lovell, 2000; and Coelli et al., 2005).

As stated by Kumbhakar (1988), Kumbhakar (1990) and Kumbhakar et al. (2013) this frontier function introduced the concept of technical inefficiency to bridge the gap between actual costs and minimum feasible costs. Kumbhakar et al. (2015) explained further that the cost efficiency frontier can be defined as the potential minimum cost, and the actual cost moving above the minimum frontier owing to inefficiency. An airport specific empirical application of the stochastic frontier cost efficiency analysis is provided in the next section.

2.2 A generalization of the SFA models

Since cost is the core of all economic analyses much of the current growing research is concentrating on cost efficiency. Advanced techniques of separating persistent inefficiency from transient inefficiency have also been introduced in literature. Hence, cost efficiency in service provision (Filippini and Hunt, 2016), can be applied by selecting a combination of inputs that minimize production costs and consider the least cost technology. In an analysis of US' electricity efficiency, Filippini and Hunt (2016) investigated demand modeling and a frontier analysis at both aggregate and sectoral levels. They addressed technical inefficiency and the problem of unobserved heterogeneity using the Mundlak Random Effects Model (MREM) that focuses on persistent efficiency and the True Random Effects Model (TREM) which focuses on transient efficiency. Filippini et al. (2018) separated firms' level of persistent and transient cost efficiency using the generalized true random effects (GTRE) model and compared the results with a true random effects (TRE) model's specification as a benchmark for the transient level of cost efficiency. They found that the GTRE model ensured and separated the presence of persistent as well as transient cost inefficiencies. Similarly, Filippini and Greene (2016) were also separated persistent and transient productive inefficiency using a maximum simulated likelihood approach.

Badunenko and Kumbhakar (2017) applied multiple approaches and perspectives for addressing the four component heteroskedastic panel data stochastic frontier model and identifying the determinants of persistent and time-varying inefficiencies. They found that as ownership types vary, firms adjust differently to changes in the regulatory conditions in the banking system.

On the other hand, Tsionas and Kumbhakar (2014) identified unobserved firm effects, that is, firm heterogeneity from persistent or time-invariant/long-term and transient or time-varying/ short-term technical inefficiency in a four-way error component model. They applied the Bayesian methods of inference as a generalized true random effects (GTRE) model for the robustness of the model and efficiency methods for estimating inefficiency validated by the Monte Carlo test's results. They confirmed that the GTRE model performed well and compared this to the returns to scale, technical changes, and technical inefficiency with two competing models -- the standard stochastic frontier and true random effects models. Their approach is similar with the analysis of airports' cost efficiency in terms of true fixed effects, ML, and distance efficiency effects applied in this study.

Tsionas and Kumbhakar (2014) focused more on a standard panel data analysis for controlling firm heterogeneity due to the unobserved time-invariant covariates. While in previous literatures such as Kumbhakar, 1987; Pitt and Lee, 1981; and Schmidt and sickles, 1984 treated time invariant firm effects as fixed parameters. Later, the concept improved and Kumbhakar (1991), Kumbhakar and Heshmati (1995), and Kumbhakar and Hjalmarsson (1995) considered persistent inefficiency including another random component for capturing time-varying technical inefficiency. All these formulations are totally different from the TR or TF effect models proposed by Greene (2005a, 2005b). In the true fixed/random effects model, firm effects are not assumed to be a part of the inefficiency. Makieła (2017) applied a generalized true random effects model (GTRE) using a Bayesian approach following Gibbs sampling. His results showed that the transient and persistent inefficiency components were approximated by the simple Gibbs sampling procedures. Makieła (2017) also indicated that the relationship between inefficiency found in GTRE, true random effects (TRE), generalized stochastic frontier, and standard stochastic frontier models needed further research.

Badunenko and Kumbhakar (2016) examined when, where, and how one can use these models with confidence for estimating persistent and transient inefficiencies. They evaluated all advanced approaches, techniques, and models. They raised concerns and addressed them in terms of a series of simulated models and found that even the GTRE model did not uniformly and overwhelmingly outperform the simpler models. They concluded that this should not discourage the development of efficiency analyses and instead the obtained estimated results should be treated with due care as this is crucial and according to them failure to do so might make technical efficiency estimates useless.

2.3 Empirical applications of the models to the airport industry

This literature review focuses on the use of the stochastic frontier analysis (SFA) and data envelopment analysis (DEA) as applied to the air transport industry all over the world. Some of the airport-specific studies and their findings are now discussed. DEA is a non-parametric analysis and as such is different from the parametric SFA. A review of both as discussed in literature is helpful in modeling the air transport industry and studying its performance using the two approaches.

An empirical review applying the frontier method to the cost efficiency frontier was developed within an overall production theory framework. Some of the advancements in stochastic frontiers focused on cost efficiency analyses.

McCarthy (2011) analyzed 50 large and medium hub airports in the US covering the 13-year period 1996–2008. The study estimated a flexible translog functional form of airports' operating cost models using one and two outputs for the short-run. It considered annual passengers served and cargo freight shipped as outputs and the number of runways as a quasi-fixed factor of production. Basically, he examined a cost model using three increasing complex models -- one-output (passenger) with and without non-aeronautical airport activities and two-outputs of passengers and freight models that accounted for non-aeronautical airport activities respectively. McCarthy's (2011) findings showed that the one-output model with non-aeronautical attributes was robust as compared to the assumed base model. Following the two-outputs model they found that economies of capacity utilization and the marginal costs of serving additional passengers were less than the average cost of serving passengers. Similarly, an increase in the runway capacity reduced short-run operating costs with statistically insignificant effects. In general, McCarthy (2011) concluded that an airport's cost can increase or decrease because of various reasons. For instance, accidents and terrorist attacks (like the September 11, 2001 terrorist attacks) can increase airports' operating costs while economic developments in an airport's geographical location reduce its average costs. McCarthy (2011) also found that input demand for any airport's operations was price elastic so a decrease in an airport's real average operating costs was associated with increasing metropolitan areas and employment there, an increase in the number of establishments, state service provisions, and industrial output, assuming other things as constant.

In addition to the functional form, the effects of the differences in ownership on efficiency was studied in all US public sector and commercial airports by Kutlu and McCarthy (2016). They used the stochastic frontier approach for the medium and large hub airports and found that the type of ownership mattered for cost efficiency. According to them, public sector ownership had higher costs in some environments.

Besides, when their study controlled for the uncontrolled heterogeneity effects this substantially changed from a small effect to a significant effect.

Fageda and Voltes-Dorta (2012) studied the cost and revenue efficiency of Spanish airports by comparing them to the other world airports. They took into account financial and traffic data on airports worldwide based on a sample composite non-standard profit function approach for estimating the cost and revenue efficiencies of Spanish airports. Their findings showed that the losses observed by small airports (less than 500,000 passengers) were largely due to revenue inefficiencies which partially happened due to rigid individualized management systems for aeronautical revenue management and an inadequate promotion of retail activities. They underlined the importance of disaggregation of aeronautical and non-aeronautical revenues. According to their analysis this separation of revenue streams improved the characterization and impact of managerial factors such as ownership or price regulations on aeronautical revenue's efficiency. To estimate marginal costs, efficiency levels, and scale elasticities, Martín and Voltes-Dorta (2011) developed an airport-specific methodology for estimating a multi-output long-run cost function for 161 airports worldwide. Their model specified technical and allocative inefficiencies using a SF method that was estimated following the Bayesian Inference and Markov Chain Monte Carlo approaches. Martín and Voltes-Dorta (2011) identified hedonically-adjusted aircraft operations, domestic and international passengers, cargo, and commercial revenue as output vectors.

Zhao et al. (2014) did a study of the publicly owned airports in the United States and Canada using the stochastic cost frontier model for a panel of 54 major airports covering the period 2002-08. Their study examined how the operations and governance by the government's branch or airport authority effected the efficiency of public airports. Their findings implied that airports operated by the airport authority had higher cost efficiency than airports operated by government branches. In terms of the labor's share, airports operated by government branches achieved a lower labor share than those owned by the airport authority. With regard to efficiency, there was no statistically significant difference between airports operated by the US airport authority and those operated by the Canadian airport authority.

Liebert (2011) used parametric and non-parametric approaches for world airports to estimate their productivity and efficiency. He focused on the heterogeneous character of the airports and found that airports which did not have market competition ought to control their cost efficiencies and regulate their monopoly power in the market.

Ulku (2009) discusses how the efficiency for LCCs (low cost carriers) increased in importance in Germany. He indicated that whenever there was excess capacity, airports which had LCC traffic generated higher outputs by decreasing their extra costs. Besides, airports which had undertaken capacity expansion recently became less efficient. Following this finding, his economic theory and empirical analysis suggested that 'efficiency can be achieved if there is proper management of existing resources. As a result, an airport's management is entrusted with the development of both short-term and long-term strategies for achieving specific goals. Hence, the airport's management is responsible for prioritizing and categorizing services according to its economic, political, operational, and financial conditions. According to Ulku (2009) analyzing the returns to scale model showed that Asian airports were ranked first and Latin American airports stood second in rank in terms of variable returns to scale (VRS). He estimated the truncated regression and found that hub and airports located in cities with less than a 5 million populations were also more efficient than airports in smaller cities and airports having more non-aeronautical revenue sources were also more efficient than the others.

Bottasso et al.'s (2012) empirical results were consistent with their hypothesis and the conspicuous entry of LCCs in European markets which positively impacted airports' productivity. This result was robust and implied that the most efficient airports were those that were more likely to attract LCCs. Thus, airports were expected to adapt to changes introduced as a result of liberalization of the airline industry. These changes were in favor of LCCs since they created pressure on airports to reduce costs and go in for productivity improvements which were necessary for attracting LCCs and for increasing their market share in the competitive environment. The authors argue that LCCs have a dual benefit for airports' performance which is mutually reinforcing. Firstly, an increase in traffic volume has a positive and direct effect on an airport's revenues in the form of aeronautical and non-aeronautical activities. Secondly, the introduction of a new competitive environment among airports induces strong pressure to reduce airline charges. This can effect airports' financial performance negatively and force airports to restructure and streamline their strategic activities. The introduction of such dynamic approaches has benefitted airports in actual cost reductions and productivity improvements.

Due to increasing globalization and international tourism, air transport traffic has increased significantly during the last four-five decades (Liebert, 2011). This means that even when there was an external shock and economic downturn like the 2007-08 financial crisis and the terror attacks in the US in 2001, the aviation industry was not impacted except for minor temporary interruptions. Instead, gradual liberalization of the airline industry which began at the end of the 1970s enabled airlines to reduce airfares. This was considered a major change in the sector. Due to airlines' deregulation, many airports started experiencing increasing exposure to cost pressures which obliged airlines to implement and operate efficiently.

Bottasso et al. (2012) applied the panel data total factor productivity (TFP) approach for studying UK's largest airports during the period 2002-05. Their empirical analysis followed a two-step approach, where TFP was estimated using different econometric techniques in the first stage and, in the second step a dynamic panel data model of an airport TFP was estimated by regressing the first step fitted values of TFP to a set of explanatory variables including ownership forms, airport specific characteristics, and the share of LCCs in total passengers. Structural adjustments in ownership and government structures, different organizational models, and new vertical relationships between airports and airlines were some of the adjustments made by the European airport industry in general and by the UK in particular. In their analysis, the authors controlled for airport unobserved heterogeneity, market level trends, and reverse causality issues.

Heshmati et al. (2016) used the parametric approach in the stochastic cost efficiency approach to investigate international airlines for the period 1998-2012 using the advanced stochastic frontier (SF) panel data methodology. Their model was estimated using the maximum likelihood method and they estimated persistent, transient, and overall efficiency scores for each airline in the study's time period. Their findings showed that none of the airlines achieved the expected minimum cost efficiency. Besides, there was a difference in efficiency levels among airlines. Further, their study identified the model's specifications and location/geographical areas of airlines as the main sources for the differences in their efficiency levels. In addition, their study found that different types of market structures, deregulation processes at airports and for airlines, and some specific competitive conditions (that is, resource availability and strategic alliances with competitors) also explained the differences in their performance. Even though the bigger airlines were not working to full economies of scale and were also not more efficient as compared to their smaller partners, their final finding showed that low cost carriers in the Asia region were more efficient than others.

Within the framework of parametric as well as non-parametric approaches, a number of studies on airport efficiency have been done in the recent past. Liebert (2011) showed that even though the appropriate measures of capital have not been resolved, a methodical application of airports research was significantly progressing. He combined the impact of an airport's ownership form, economic regulations in the countries, competition, and pricing at airports in two steps. The first step involved using the non-parametric DEA approach while the second step was a regression analysis of environmental aspects. His findings showed that in a competitive environment, regulations prevented airports from operating efficiently. Thus, airports which had no competition should be regulated to increase their cost efficiency and preventing market exploitation. This implies that private airports were making profits without competition in the absence of regulatory restrictions. Liebert (2011) summarized that with an increase in commercialization, privatization activities, change in economic regulations, and restructuring there were significant changes in the industry.

As a consequence, airports' performance measurement has become an increasingly important issue in comparing airports with their competitors and for assessing efficiency changes as a result of changes in their structures. Liebert (2011), and Liebert and Niemeier (2010) highlighted the core development of structural changes since the 1970s and that economists had been debating if there was a need to regulate the airline industry and whether political restrictions constrained the relationship between passenger growth and technological advances. The heavy-handed regulation of domestic routes, fares, and schedules was removed in the US in 1978. In 1993, restrictions on routes, capacities, and market entries were totally removed within the European Union. Further, the liberalization process reached a significant stage for the first time when the EU-US open sky agreement became effective in March 2008.

Some efficiency challenges included several airlines complaining about ground handling services. Ground handling services comprise important activities such as handling passengers, baggage, freight and mail, ramp handling, aircraft service and maintenance, and handling fuel and oil (Graham, 2005, 2013 and 2014; Liebert, 2011). In most cases such services were regulated and were owned by the countries' national carriers giving them market power which led to excessive exploitation of other airlines. Understanding such consequences for the other airlines, the liberalization of airport ground handling services was deregulated in 1996 throughout the European Union (EU). Accordingly, a EU directive allowed airlines and independent third parties to participate in ground handling services and reduce the monopoly power of the national carriers. This had a significant impact in improving the efficiency of services at airports.

According to Liebert (2011) airport charges that the public authorities charged was done in a fully regulated environment through the civil aviation authorities. This regulation had implications for political restrictions, market entry restrictions, air ticket fares, capacities, and frequency protection of the national carriers in a contestable market environment that was characterized by low economies of the scale. The price cap concept which was initially proposed by Littlechild (1983) and introduced for implementation in the regulated British Airport Authority's (BAA) airports with the concept of privatization for a regulated period of five years. The price cap regulation formula RPI-X (retail price inflation minus expected efficiency improvements) represents the retail price index and X is the efficiency improvement that reasonably considered the timeframe as decided by the regulatory body. In such cases, airport management achieved higher cost reductions over the five-year period. According to Liebert as the power of the market was increasingly exploited, airports started facing competition from nearby airports or other modes of transport with regulated airport prices commonly practiced throughout world airports.

3. Dataset and Model Specifications

3.1 Data and description of variables

The aviation industry in general and airports in particular produce and use various types of outputs and inputs. Literature refers to the number of passengers and cargo transported in kg as output variables of the aviation industry. Provision of passenger and cargo transportation services also has costs in terms of employee wages and salaries, maintenance and repairing costs, and other miscellaneous costs.

To achieve the research objective of this dissertation, the following time series data was obtained from the Ethiopian Airport (EA). The data has annual records of Ethiopian airports and some data from the National Bank of Ethiopia including panel data for the balance sheets for the period 2002-17. The remaining airports are in a nascent stage (less than 10-years old) having short time series data. The number of observations could be increased with an increase in the timespan and by considering 16 years as the cut off period as a result of which the number of observations went up to 13 airports; 208 observations were used in the analysis. Hence, 13 of the 23 currently operating national airports formed a part of this study. The period of the establishment of the airports varied but with well-equipped facilities their average age ranged between 16 and 20 years except for Addis Ababa Bole (ADD) International Airport which has been operational since the 1960s. Mekelle, Bahir Dar, and Dire Dawa are the other international airports in the country.

The data is organized based on the airports' economic relationships and inclusiveness for explaining the dependent variable. The dependent variable (total cost) is an aggregated cost of operating expenses, employees' salaries and wages, and repairing and maintenance costs of fixed capital assets. A stochastic cost frontier panel data analysis was done for two output and three input prices.

3.2 Input prices of airport services

Infrastructure at and operations of airports requires various inputs each of which costs. Some studies such as those by Martín and Voltes-Dorta (2011) show that calculating and determining input prices at airports is a delicate and complex exercise. Hence, categorizing these activities makes easier to do an analysis. The three commonly known input categories are labor, materials and outsourcing (OS) activities, and capital (Martín and Voltes-Dorta, 2011). Their associated prices are determined by dividing the respective costs by the quantity indices which are the same as aggregated input demands. Due to the difficulties in aggregating details, inputs quantity and unit price, this study considered proxy input prices as energy prices, capital prices taking world crude oil prices, sum of aggregated fixed asset prices with the domestic capital investment lending rate which is similar to Greene (2005a) who used the long-term interest rate as the price of capital of banks. Price of labor was directly calculated by taking real value of employee salaries and dividing it by the annual number of employees.

Average annual world prices of crude oil (PE) per gallon/barrel represents the real price of energy. Airport facilities and airlines consume huge quantities of energy. This has an indirect impact on increasing airport costs. It also has a direct and negative influence on passenger and cargo freight transport.

Real price of labor (PL) is represented by the real value of annual wages and salaries of employees divided by annual total effective working hours. It is the real price of labor per productive hour which is annual salaries and wages of employees per man-day productive hours (L) which was calculated as the actual number of workers multiplied by annual working hours. Effective working refers to working hours excluding weekends and annual leave.

Capital investments in an airport include investments in the passenger terminal building, the cargo terminal, runway, taxiway and apron construction, and installation and construction of complementary facilities such as a powerhouse and a large cold-room warehouse. These have a lifespan of more than 20 years. There are also other fixed assets such as machinery, vehicles, office equipment, systems, and software which are very crucial for the operations of airport services; they have a lifespan of approximately 5 years.

Price of capital (PK) in this study is defined as the real price of the domestic lending interest rate. It is calculated by finding the difference between the nominal interest rate and the inflation growth rate. The price of assets is calculated from the real value of the fixed assets' depreciation. The price of capital and fixed assets is the summation of the variables lending rate plus the growth rate of inflation and the depreciation rate.

3.3 Airport services

Estimating a cost frontier requires specifying an output vector. However, the multi-output nature of transport firms has been typically neglected in empirical studies due to lack of data, which led to the use of output aggregates (Jara-Díaz, 2007). The specification of disaggregated outputs allows output-specific marginal costs to be estimated based on which an analysis of optimal pricing and investments is based. Besides, in the event that an airport's activities (airside, landside, retail) are regulated and managed independently, calculating the output-specific scale economies is essential for assessing the optimal airport size. The size could be totally different in an environment in which all the activities are under the umbrella of the airport authority (Martín and Voltes-Dorta, 2011). For these reasons, this paper proposes two-output specifications of the cost function.

Airports do not provide transportation directly but provide all the necessary infrastructure for air traffic. Their multi-product nature is related to the different uses that aircraft, passengers/baggage, and freight make of the facilities available for generating revenue. Hence, a two-dimensional outputs vector (passengers (YP), freight cargo (YC)) can be considered for studying an airport's cost functions.

3.4 Passengers and Freight Cargo

The output of the air transport industry are the passengers and cargo freight transported and aircraft movements which is a joint operation of carriers and airports. Infrastructure costs of a passenger terminal are slightly higher than those of a freight cargo terminal. Given that Ethiopia is a landlocked country, demand and volume of freight cargo is extremely high which necessitated a separate cargo terminal at Addis Ababa Bole International Airport. The passenger and cargo terminals along with other facilities generate revenue for the airports and airlines based on their share in providing the services. The summary statistics in Table 1.1 are categorized in such way that the cost function is a dependent variable whereas annual passengers served by each airport and freight cargo transported in kg between the origin and destination are considered as output variables of the cost function.

Table 1.1. Ethiopian airports' output and input price data summary (2002-17) (NT= 208 observations, in 2009 constant prices)

Variable	Descriptions	Mean	Std. Dev	Minimum	Maximum	CV
Cost	Total Cost in Birr	5,971,349	13,100,000	320,000	65,300,000	2.20
Yp	Total passenger movement in number	408,839.40	1,426,697	1,197	10,200,000	3.49

Yc	Cargo fright in kg	11,400,000	4,040,000	1.00	243,000,000	3.53
PE	Average world crude oil prices in Birr	18,282.38	14,934.5	2,403.56	44,190.52	0.82
PL	Price of labor	26.76	7.52	9.61	43.90	0.28
PK	Price of capital and fixed assets	0.47	0.14	0.06	0.62	0.30

Source: Author's ccalculations based on data from Ethiopian Airports (2018) and National Bank of Ethiopia (2016-2018)

Summary statistics for major airport input prices are price for the labor force, energy price, and price of capital. The real value of wages and salaries for each airport per effective working hour ranged between 9.6 to 44.0 Birr (ETB) per hour during the study period 2002-17 with an average of 26.76 Birr per effective working hour. Similarly, the price of energy which is represented by the average world oil prices converted to Birr with the annual average exchange rate (in constant prices). Accordingly, the average real price of energy during the study period was about 18,282.38 Birr with minimum of 2,403.56 Birr and a maximum of 44,190.52 Birr per gallon during the study period. While the price of capital assets with an assumption of the domestic lending rate and a standard depreciation rate was effected by the inflation rate in the country. This shows that the price of capital and fixed assets was between 6 percent and 62 percent with an average capital price of 47 percent.

Table 1.2 shows that the number of passengers and number of aircraft movements per year varied between the minimum and maximum values. Similarly, the standard deviation was very high compared to the mean production. This means that there are extremely high variations across airports and there has been significant growth in airports over time. The covariance of total passengers measured by the number of passengers and cargo freight in kg was 3.49 and 3.53 respectively.

Finally, considering the data quality, all necessary data assurances were done through internal and external financial auditing. As a common practice, financial data is approved by an external auditor on a yearly basis while other passenger/cargo and aircraft movements are recognized by the Airport Council International (ACI). Service related data collected for this research is on a monthly basis reported to the Airport Council International and the International Civil Aviation Organization (ICAO) while the financial data is approved by an annual audit report of the National Audit Service Corporation.

Table 1.2. Summary of the variables used in the estimation (in logarithmic form)

Variables	Mean	Std. Dev	Minimum	Maximum	CV
Logarithm of total cost in ETB	14.57	1.26	10.52	17.99	0.09
Logarithm of total passenger movement in number (lnYp)	10.81	1.71	7.09	16.14	0.16
Logarithm of cargo freight in Kg lnYc	8.70	5.37	0.00	19.31	0.62
Logarithm of average world crude oil prices in Birr (lnPE)	3.27	0.45	0.38	4.48	0.14
Logarithm of price of labor (lnPL)	-0.87	0.57	-2.89	-0.49	-0.66
Logarithm of price of capital and fixed assets (lnPK)	6.82	0.67	5.64	7.58	0.10

Source: Author's ccalculations based on data from Ethiopian Airports (2018), National Bank of Ethiopia (2016-18)

3.5 Airport facilities and services

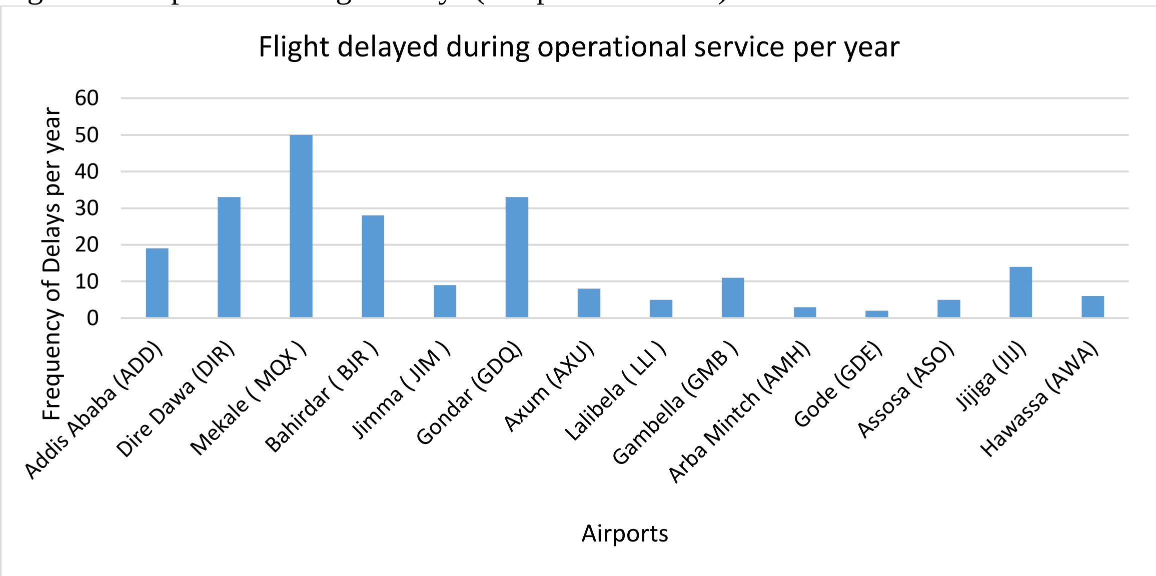
At the Addis Ababa Bole International Airport hub, on average there were more than 127 international and domestic departures (EAG Factsheet, November, 2019). These flights used 14 boarding gates at Terminal two and Terminal one and additional boarding from 21 remote gates. Besides, there are 100 aircraft stands in the apron area at the airport. There are 14 and 60 passenger checking counters at Terminal one and Terminal two respectively (EAG, 2019). As of June 2018, nearly 450 flights per day departed from and arrived at the airport.

Two major infrastructure expansion projects were undertaken at the airport which were partially operational at the end of 2019. The first is a large investment in the airport terminal's expansion and the second is for expanding the ramp area for additional aircraft standing/equipment parking area and additional taxiways. With this major expansion work, the capacity of Addis Ababa Bole International Airport increased to 22 million passengers per annum (EAG, 2019).

The ongoing and partially operational additional aircraft landing, apron parking, runway lighting, boarding bridge, passenger X-rays, and ground handling which form a part of aeronautical services will lead to an increase in revenues and associated costs for the airport. Similarly, as the terminal area expands, revenue and related costs of aeronautical and non-aeronautical services (rentals, food and beverage recreational area services, and car parking and porter services) will also increase (EAG, 2019).

The ground handling services provided at Addis Ababa airport mainly focus on supporting Ethiopian's operations while excess capacity has been a source of revenue for the airline. The overall performance of the ground handling services in terms of supporting the airline's operations at the main hub forms a lion's share as compared to the income generated by providing services to other airlines. As indicated in the EAG annual report (2018), increased by 41 percent, 9 percent, 1 percent, -14 percent, and 12 percent for five years since 2011-12. An increase in the number of flights by some of the scheduled operators for passengers and cargo and new entrants along with increased ad-hoc flights helped to substantially increase the airport's revenue. In addition, the service standards required by customers helped the ground handling unit to upgrade its services.

Figure 1.1. Operational flight delays (sample from 2017)



Source: Author's calculations based on data from Ethiopian Airports (2019)

Notwithstanding this, the percentage recorded delay in flights as compared to on-time flights was very low, less than 1 percent per year (see Figure 1.1). The longest delay recorded in 2017 was at Mekelle Airport (about 50 flights delayed) and the second and third highest delays were recorded at Dire Dawa and Gonder airports respectively (more than 30 flight delays).

4. Model Specification and Efficiency Measurement Approaches

Measuring an airport's performance using a panel data model follows two main approaches. The first one is parametric (econometric) which includes the SFA model. The second is non-parametric and is mostly represented by DEA. As stipulated by Alem (2018), both approaches follow the radial contraction/expansion of observed actual inefficiency points compared to the potential reference points on the frontier. The basic distinction between the two approaches are the measurement and random errors. In the stochastic frontier model, stochastic noise is considered as a measurement error in an airport's service provisions due to environment hazards such as bird hits, weather conditions as the airport may have heavy rain, wind, and ice, distance from the nearby city, airport infrastructure, and access to airport. The frontier is random and as such can be lower than the actual observations.

In addition to the random error, the airport industry is highly sensitive to internal and external shocks particularly safety and security, market competition, and the urban nature of its location. Under these circumstances, using the SFA approach for estimating the cost efficiency score is preferable as it is a better model. SFA has the advantage that it models input-output relationships and controls for producing unit, market, environmental, and regulatory characteristics. The cost efficiency score of a SFA model assumes that an airport which is cost efficient is the best airport while the remaining airports are operating at cost inefficient levels that are above the cost frontier line or above the minimum estimated cost boundary.

Following the introduction of the SFA panel data model which has a one sided inefficiency, several researchers developed consistent and unbiased estimates based on various assumptions. Alem (2018) discusses some assumptions about the temporal behavior of inefficiency, the specifications of the model, distributional assumptions, and techniques for estimating the model selection. However, Karagiannis and Tzouvelekas (2002, 2009) state that no model has an absolute advantage over the others and hence selecting the best SF model for an efficiency analysis is a highly complex exercise. Moreover, there are no clear-cut statistical criteria for preferring one model over the others. Hence, in many cases the choice and analyses are done with significant justification of the respective model assumptions.

The cost model specified in this chapter is a cross-sectional stochastic frontier model following Aigner et al.'s (1977) proposed model as:

(1.6) $Cost = f(Yp, Yc, PL, PE, PK)$

where total cost is annual total operating and administrative cost, maintenance and repairing expenses including salaries and wages given by each airport, Yp is annual total passenger output movement at each airport, Yc is the annual freight cargo output transported, PL is the price of labor per man-days' productive hours excluding annual leave, weekends, and holidays, and PE is real crude oil prices/ prices of energy and PK is the sum of the domestic real interest rate and the price of fixed assets is represented by the price of capital and price of fixed assets.

The simplest functional relationship frequently used in economics is a Cobb-Douglas production function. This study applies a log linear Cobb-Douglas type cost function. The cost function with the 3-input prices and 2-outputs duality function takes the form:

(1.7) $Cost = \alpha_0 Yp^{\beta_1} Yc^{\beta_2} PL^{\beta_3} PE^{\beta_4} PK^{\beta_5} e^{\varepsilon}$

where the total cost is a function of two outputs (passenger and freight cargo transported), and three inputs (price of energy, price of capital, and price of labor). In Equation (1.7) the parameters α_0 and β_0 are positive and constant, where $i \geq 1$. The term e^{ε} represents the error term. This type of cost function is linear in logarithm and useful for determining whether the inputs exhibit increasing, decreasing, or constant returns to scale.

The stochastic frontier panel data model takes the natural log of both sides of the equation and defines the cost function as:

(1.8) $\ln Cost = \alpha_0 + \beta_1 \ln Yp + \beta_2 \ln Yc + \beta_3 \ln PL + \beta_4 \ln PE + \beta_5 \ln PK + \varepsilon$

The log form of the model assuming panel data and adding time and airport subscripts is given as:

(1.9) $\ln Cost_{it} = \alpha_0 + \beta_1 \ln Yp_{it} + \beta_2 \ln Yc_{it} + \beta_3 \ln PL_{it} + \beta_4 \ln PE_{it} + \beta_5 \ln PK_{it} + \varepsilon_{it}$

The error term of the cost frontier model can be decomposed into statistical noise (v_{it}) and time-invariant inefficiency (u_i) i.e. $\varepsilon_{it} = v_{it} + u_i$. The level of inefficiency may be greater than long-run or persistent inefficiency.

Decomposing the deviation of the error term to capture time varying efficiency, the panel data cost function with time trend (Year) is expressed as:

(1.10)

$$\ln Cost_{it} = \alpha_0 + \beta_1 \ln Yp_{it} + \beta_2 \ln Yc_{it} + \beta_3 \ln PL_{it} + \beta_4 \ln PE_{it} + \beta_5 \ln PK_{it} + Year_t + v_{it} + u_{it}$$

In these equations, $\ln Cost_{it}$ represents the logarithm of total cost as the dependent variable. The independent variables are $\ln Yp_{it}$ log of passenger movements, and $\ln Yc_{it}$ log of freight cargo as production output transported respectively while the other input variables are $\ln PE_{it}$ log of price of energy, $\ln PL_{it}$ log of price of labor, and $\ln PK_{it}$ log of sum of price of capital and price of fixed assets. The variable *Year* captures the trend or unobserved technology change effects on cost.

The technical inefficiency effect of the stochastic frontier panel data model developed by Battese and Coelli (1995) was adopted in this dissertation which is similar to the stochastic frontier cost function as mentioned in Equation (1.10). The distinguishing characteristic of this model is that it estimates the cost model, observation specific inefficiency, and the effects of the determinants of inefficiency in one step using the maximum likelihood method.

The time-variant technical inefficiency effect (u_{it}) in the stochastic frontier approach mentioned earlier as specified for an airport's cost inefficiency function is written as:

(1.11) $u_{it} = \delta_0 + \delta_1 \ln Z_{1t} + \delta_2 \ln Z_{2t} + W_{it}$

where $\ln Z_{1t}$ is the log of aircraft movements per year at each airport and $\ln Z_{2t}$ is airport standard category as per ICAO. Throughout the world, acceptance and standard categories are provided regularly by ICAO based on the facilities and infrastructure that airports own. Reduction in any one of the facilities such as apron fire truck and runway lighting results in lowering the airport's category for a specified period of time.

Here the random variable W_{it} is defined by the truncation of the normal distribution with zero mean and constant variance (δ^2) and the point of truncation is ($-Z_{it}\delta^2$), that is, $W_{it} \geq -Z_{it}\delta^2$ which is consistent with the assumptions underlying u_{it}.

The technical cost efficiency of the 13 airports at time period t is defined as:

(1.12) $TE_{it} = \exp(-u_{it}) = \exp(-Z_{it}\delta - W_{it})$

Hence technical efficiency is also based on conditional expectations according to the assumption of the model.

The marginal effects of inefficiency as shown by Wang (2002) can also be found from the cost frontier with features of KGMHLBC and CFCFGH models in Equation (1.10) and the efficiency term can be defined as:

(1.13) $u_{it} \neg N(0, \sigma_u^2)$,

(1.14) $u_{it} \neg N^+(\mu_{it}, \sigma_{it}^2)$,

(1.15) $\mu_{it} = Z_{it}\delta$,

(1.16) $\sigma_{it}^2 = \exp(Z_{it}\gamma)$.

where u_{it} is the inefficiency effect indicating a non-negative truncation of a normal random variable and the variables z_{it} are constant values associated with inefficiency with δ and γ as the corresponding coefficients. Wang's (2002) model is developed as a special case of KGMHLBC and CFCFGH (hereafter Kumbhakar, Ghosh, and McGuckin (1991), Huang and Liu (1994), and Battese and Coelli (1995) as KGMHLBC; and Caudill and Ford (1993), Caudill, Ford, and Gropper (1995), and Hadri (1999) as CFCFGH). According to Wang (2002), KGMHLBC applies by replacing z_{it} using a constant number 1 in Equation (1.16) and substituting 0 for CFCFGH in Equation (1.15), even though Kumbhakar and Wang (2010) state that the boundary between the two is blurred.

Kumbhakar and Wang (2010) summarized the marginal effects of the mean and variance of inefficiency (u_{it}) respectively as:

(1.17) $$\frac{\partial E(u_{it})}{\partial z[k]} = E'(u_{it}) = f'(\mu_{it}, \sigma_{it}) = \sigma_{it}[k]\left[\frac{\mu_{it}}{\sigma_{it}} + \frac{\phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}\right]$$

(1.18) $$\frac{\partial V(u_{it})}{\partial z[k]} = V'(u_{it}) = g'(\mu_{it}, \sigma_{it}) = \sigma_{it}[k]\left[1 - \frac{\mu_{it}}{\sigma_{it}}\left[\frac{\phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}\right] - \left[\frac{\mu_{it}}{\sigma_{it}} + \frac{\phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}\right]^2\right]$$

hence ϕ is the probability density and Φ are cumulative distribution functions of a standard normal variable. Both equations imply that the mean and variance of u_{it} are expressed as functions of μ_{it} and σ_{it}. They are observation-specific and have an exogenous influence in both the cases.

Though different models have been developed based on the various assumptions of inefficiency, it is noted that technical efficiencies are constant in the first model and vary over time in the other model during an analysis of the four panel data stochastic cost frontier models listed in Table 1.3. Further decomposition and estimation of efficiency applied to the five panel data models are shown in Table 1.3.

Table 1.3. Four fitted panel data models' specifications for airports' cost efficiency

Model	Model specifications	Inefficiency assumptions	Inefficiency (SR/LR)
Model 1: Fixed Effects (FE)	$\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + yr_t + v_{it} + u_i$ $\ln C_{it} = (\alpha_0 + u_i) + f(Y_{nt}.P_{nt};\beta) + yr_t + v_{it}$ $\ln C = \alpha_i + f(Y_{nt}.P_{nt};\beta) + yr_t + v_{it}$	Time-invariant $\hat{u}_i$ is the fixed effects distribution assumption of u_i	Long-run/persistent inefficiency $\hat{u}_i = \hat{\alpha}_i - \min_i\{\hat{\alpha}_i\} \geq 0$
Model 2: Greene (2005a) TFE	$\ln C_{it} = \alpha_i + f(Y_{nt}.P_{nt};\beta) + \varepsilon_{it}$ $\varepsilon_{it} = v_{it} + u_i$ $\alpha_i = (\alpha + \mu)$ where α_i is treated as fixed parameters	Time varying $u_i \sim N^+[\mu, \sigma_u^2]$ $v_i \sim N^+[0, \sigma_v^2]$	Short-run/transient inefficiency $E(u_i / v_{it} + u_i)$
Model 3: Kumbhakar et al. (2014), KLH-2014	$\ln C_{it} = \alpha_0^* + f(Y_{nt}.P_{nt};\beta) + yr_t + \alpha_i + \varepsilon_{it}$ $\varepsilon_{it} = v_{it} + u_{it} + E(u_{it})$ $\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it})$ $\alpha_i = \mu_i - \eta_i + E(\eta_i)$ and μ_i is the firm specific effects	$u_i \sim N^+[\mu, \sigma_u^2]$ $v_i \sim N^+[0, \sigma_v^2]$ $\mu_i \sim N^+[0, \sigma_\mu^2]$ $\eta_i \sim N^+[0, \sigma_\eta^2]$	Long-run/persistent inefficiency $E(\eta_i / \mu_i - \eta_i)$ Short-run/transient inefficiency $E(u_{it} / v_{it} + u_i)$

Model 4: Battese and Coelli (1995), BC-1995	$\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + yr_t + v_{it} + u_i$ $\varepsilon_{it} = v_{it} + u_i$	Time varying and truncation normal distribution $u_{it} \sim N[Z_{it}\delta, \delta^2]$ $v_{it} \sim N[0, \sigma_v^2]$ $w_{it} \sim N[0, \sigma_w^2]$	Technical inefficiency effects $u_{it} = z_{it}\delta + W_{it}$

Model 1: The Time-invariant Fixed Effects model

This study starts with the time-invariant individual-specific fixed effects model which allows an estimation without distribution (distribution free assumptions). Accordingly, the time-invariant fixed effects (FE) model as proposed by Schmidt and Sickles (1984) is similar to the standard fixed effects model and is estimated by applying the standard estimation methods. As explained by Parmeter and Kumbhakar (2014) the standard FE panel data model can provide consistent estimates of β though $\hat{\alpha}_i$ is a biased estimator of u_i since $u_i > 0$ by construction and α_i are treated as fixed and unobserved individual effects of the model .

With the fixed effects framework, u_i is allowed to freely correlate with x_{it} in the model. As stated by Mundlak (1961) fixed (inefficiency) effects are believed to be correlated with the inputs under consideration which also have desirable properties of empirical applications in such models. The FE approach on the other hand excludes other time-invariant variables (regressors) such as location of an airport based on the explanatory variable x_{it} so as to avoid perfect multi-collinearity with unobserved individual effects α_i (Kumbhakar et al., 2015; Parmeter and Kumbhakar, 2014).

Hence, the fixed effects model is estimated using ordinary least squares (OLS) by including individual dummies to capture α_i which is called the least square dummy variable (LSDV) model. The coefficients of the dummies are estimates of α_i. In the LSDV assumption, each cross-sectional unit has one fixed effects parameter and the number of dummies to be included in the model is equal to the number of cross-sectional units. This implies a $(N+K)\text{x}(N+K)$ covariance matrix where N is the number of cross-sectional units and K is the number of regressors' x_{it} variables. A disadvantage of the FE model is that time-invariant regressions are not separated from the fixed effects.

Kumbhakar et al. (2014), Kumbhakar et al. (2015) and Parmeter and Kumbhakar (2014) state that the difficulties with this model can be managed through different techniques before removing α_i. The most common in panel data models are the first difference and/or within transformation methods. Applying either of these can easily eliminate α_i. The transformed model can be estimated using OLS. Hence, the OLS estimator of $\hat{\beta}$ is a consistent estimator of β from which the values of $\hat{\alpha}_i$ can be recovered from the residual mean of each individual cross-sectional unit. Thereafter, $\hat{\alpha}_i$ is obtained with a simple transformation to recover $\hat{u}_i > 0$ and that will also be a consistent estimator if $T \to \infty$. According to Parmeter and Kumbhakar (2014) and Kumbhakar et al. (2017), following a panel data approach of a time-invariant model, consistent estimates of β can be obtained through the transformed model as $T \to \infty$ hence, $\hat{u}_i$ is estimated based on Schmidt and Sickles (1984) model as:

(1.19) $\hat{u}_i = \hat{\alpha}_i - \min_i \{\hat{\alpha}_i\} \geq 0 \quad i = 1,...,N$

The implicit assumption of this model's formulation is that the most efficient firm/unit in the sample is considered to be 100 percent efficient while the inefficiency estimates in this fixed effects model are relative to the best firm/unit in the sample. Despite having a random error term, the efficiency scores are sensitive to outlier observations. Hence, the form of firm specific efficiency can be:

(1.20) $\hat{TE}_i = \exp(-\hat{u}_i) \quad i = 1,...,N$

Rashidghalam et al. (2016) summarized that the core limitation of the FE model is its strong assumption of time-invariant inefficiency and individual heterogeneity not being separated. Hence, the inefficiency levels vary across individuals, but never change over time. Colombi et al.'s (2011), Parmeter and Kumbhakar (2014) and Kumbhakar et al. (2015) explain that the inefficient units never changing over time mean that they do not learn over time and these inefficiencies are highly related to the firms' managerial capabilities during the study period. In reality market competition in the world is dynamic so the constant and restrictive assumption is not practical and firms can learn and change with time.

Model 2: Greene (2005a)

This model is time-varying and it is able to separate inefficiency and unobserved individual heterogeneity effects. Basically Model 2 which is also known as the Greene (2005a) true fixed effects (TFE) model follows Model 1. The basic distinction between the two lies in the treatment of α_i and its time invariant assumption of inefficiency. In Model 1 it is considered as an unobservable individual effect for obtaining the estimated value of u_i though the standard panel data fixed effects model also estimates the model's parameters including α_i. So individual or time-invariant heterogeneity which is not necessarily inefficiency is included as inefficiency because Model 1 cannot distinguish individual heterogeneity from inefficiency. These lead $\hat{u}_i$ to picking up both heterogeneity and inefficiency.

The second time-invariant assumption is criticized because it assumes that an inefficient firm might stay constant in the market for an extended period as persistent inefficiency seems implausible.

In Model 2 the cost function to be examined is written as:

(1.21) $\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + v_{it} + u_i$

Hence, Greene (2005a) separated a component from the inefficiency and treated α_i as the fixed parameters of individual heterogeneity. In this model, the error term is decomposed into three parts. The first part represents the random noise effect, the second is time-invariant unobserved heterogeneity, and the third is the firm specific time-varying inefficiency term. Filippini and Hunt (2016) explained that Greene's (2005a, 2005b) proposal of developing TFEM and TREM was for distinguishing between time-invariant unobserved heterogeneity and the time-varying firm level of the efficiency component treated as the transient part. This model is identical to Kumbhakar and Heshmati's (1995) model except it treats time-invariant inefficiency as individual heterogeneity.

Model 3: Kumbhakar et al. (2014)

This model developed a distinction between the persistent/time-invariant and transient/time-varying components of technical inefficiency simultaneously from the same data used by Colombi et al. (2014) and Kumbhakar et al. (2014). It proved that time-varying inefficiency is a short-run inefficiency of resource utilization and allocation. According to Colombi et al. (2014), Parmeter and Kumbhakar (2014), and Kumbhakar et al. (2015) and Kumbhakar et al. (2017) taking a hypothetical case of a hospital having excess capacity, short-run improvements in its efficiency can be achieved by allocating and utilizing the excess capacity of the workforce for various activities in the short-term. Such improvements have no effect on the general condition of the hospital and are independent of short-run inefficiency from the previous period's inefficiency (time-invariant inefficiency), which proves the assumption of independent and identical distribution of u_{it}.

The essence of time-invariant inefficiency in relation to persistent inefficiency mainly occurs due to the management styles of individual firms. As a result, such inefficiency cannot be resolved without changes in government policy for the industry (a change in firm-ownership and any other). Despite this, the residual component of inefficiency might change over time without any changes in a firm's operations (Kumbhakar et al., 2014).

The cost efficiency model of the study follows Kumbhakar et al. (2014) and Colombi et al.'s (2014) model which is specified and provided as:

(1.22) $\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + \eta_i + u_{it} + \mu_i + v_{it}$

Thus $\eta_i > 0$ and $u_{it} > 0$ are the two parts of the inefficiency component, μ_i and v_{it} are the other two parts (firm heterogeneity and random noise) respectively. Accordingly, Kumbhakar et al. (2014) and Heshmati et al. (2016) considered a simpler multi-step procedure as per which Equation (1.22) can be rewritten as:

(1.23) $\ln C_{it} = \alpha_0^* + f(Y_{nt}.P_{nt};\beta) + \alpha_i + \varepsilon_{it}$

where $\alpha_0^* = \alpha_0 - E(\eta) - E(u_{it})$; $\alpha_i = \mu - \eta_i + E(\eta)$ and $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$.

The error term ε_{it} can be decomposed into $\varepsilon_{it} = v_{it} + u_{it}$, where u_{it} is technical inefficiency and v_{it} is statistical noise.

Likewise, the values of α_i and ε_{it} have zero mean and constant variance. As a result, model (1.23) can be estimated in three steps:

- Step 1: estimating $\hat{\beta}$ by using the standard fixed effects panel regression approach. This model (Equation 1.23) gives the predicted values of $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$.
- Step 2: follows step one's time-varying technical inefficiency u_{it} and is estimated using the predicted values of $\hat{\varepsilon}_{it}$. The model for the second step specification is:

(1.24) $\varepsilon_{it} = v_{it} + u_{it} + E(u_{it})$

Hence, we assume v_{it} is i.i.d. $N\left[0, \sigma_v^2\right]$ and u_{it} is i.i.d. $N^+\left[\mu, \sigma_u^2\right]$ produces $E(u_{it}) = \sqrt{(2/\pi)\sigma_u}$. This means that ignoring the changes between the true and predicted values of ε_{it} is a common practice in two or more procedures. Thus, Model (Equation 1.24) can be estimated using the standard SF technique. Kumbhakar et al. (2015) assert that this process leads to predicting the time-varying residual technical inefficiency's components $\hat{u}_{it}$ where they refer to Jondrow et al. (1982) or residual technical efficiency where they refer to Battese and Coelli (1988) $\exp(-u_{it}/\varepsilon_{it})$.

- Step 3: this is the final step in estimating Model (Equation 1.23)'s term η_i. Hence, we follow the same procedure as in step two. We also apply the best linear predictor of α_i from step 1. The model is:

(1.25) $\alpha_i = \mu_i - \eta_i + E(\eta_i)$

where μ_i is assuming i.i.d. $N\left[0, \sigma_\mu^2\right]$ and η_i is i.i.d. $N^+\left[0, \sigma_\eta^2\right]$ produces $E(\eta_i) = \sqrt{(2/\pi)\sigma_\eta}$.

Equation (1.23) can be estimated using the standard normal–half-normal SF model. As Kumbhakar et al. (2015) (referring to Jondrow et al., 1982) obtained estimates of the persistent technical inefficiency component η_i. Thus, the persistent technical efficiency can then be estimated from $PTE = \exp(\eta_i)$ where $\hat{\eta}_i$ is the JLMS estimator of η_i; while an overall technical efficiency (OTE) is then obtained from the product of persistent (PTE) and residual (RTE), that is, $OTE = PTE \text{ x } RTE$.

Model 4: Battese and Coelli (1995)

The Battese and Coelli (1995) model for the technical inefficiency effect in SFA for panel data is similar to the frontier cost function and can be written as:

(1.26) $\ln C_{it} = \alpha_0 + f(Y_{nt}.P_{nt};\beta) + yr_t + v_{it} + u_{it}$

where u_{it} focuses on non-negative random variables related to the technical inefficiency of the cost function. This model assumes that u_{it} is independently distributed and its values are obtained by truncation with mean $Z_{it}\delta$ and variance δ^2, that is, $N(Z_{it}\delta, \delta^2)$. Here, Z_{it} is $(1xn)$ vector of independent variables in relation to technical inefficiency of the cost of the airport over time, while δ is the $(nx1)$ vector of unknown coefficients. The explanatory variables specified in the inefficiency model can include some inputs from the stochastic frontier model which can show that the inefficiency effects are stochastic.

According to Battese and Coelli (1995), the technical inefficiency effect u_{it} in the stochastic frontier approach (Equation 1.26) can also be specified and written as:

(1.27) $u_{it} = Z_{it}\delta + w_{it}$

where the random variable w_{it} is defined by the truncation of the normal distribution with zero mean and variance δ^2 and the point of truncation is $-Z_{it}\delta$ which is $w_{it} \geq -Z_{it}\delta$ which is consistent with assumptions of u_{it}.

According to Baten et al. (2009) the parameters of the stochastic frontier model are estimated using the maximum likelihood estimation (MLE) method. Thus, Battese and Coelli (1995) proposed the maximum likelihood method for estimating both the stochastic frontier cost model and the technical inefficiency effects model simultaneously.

The total variations in an output from the frontier level of output are attributed to technical efficiency that was considered by Battese and Coelli (1995) and Baten et al. (2009) and defined by $\gamma = \frac{\delta_u^2}{\delta_u^2 + \delta_v^2}$. As result, the variance parameter γ should lie in the interval $[0.1]$. Assuming truncated and half-normal distribution, if the ratio of airport specific variability to total variability γ is positive and significant the airport specific cost efficiency becomes important in explaining the total variability of the costs incurred. This implies that if the null hypothesis $\gamma = 0$, the technical inefficiency effect is not present in the model. Using various formal hypotheses' tests, the distribution of the random variable related to the existence of technical inefficiency and the residual error terms can be determined by using imposing restrictions and generalized likelihood ratio tests. According to Baten et al. (2009) the generalized likelihood ratio statistic can be defined as:

$$\lambda = -2(\ln[L(H_0)] - \ln[L(H_1)])$$

The values of $\ln[L(H_0)]$ and $\ln[L(H_1)]$ represent the log-likelihood function for the frontier model (within the null and alternative hypotheses). The value of the term λ will have mixed chi-square distribution considering the degree of freedom and the number of imposed restrictions.

In the cost model for 13 airports the technical efficiency at time period t is defined as:

(1.28) $TE_{it} = \exp(-u_{it}) = \exp(-Z_{it}\delta - w_{it})$.

Hence, predicting technical efficiency is also based on conditional expectations in accordance with the assumptions outlined earlier. Model 4 is an extension of the earlier generation models as it allows inefficiency to be time variant and explains the variations in inefficiency by its possible determinants. A limitation of this model is its inability to separate inefficiency into persistent and transitory components and separation of time-invariant inefficiency from firm heterogeneity. The distinguishing feature of Model 4 is that it is a random effects model while the remaining three models are fixed effects models.

Model 5: Marginal effect of inefficiency, Wang (2002)

The marginal effect of the z variable on the inefficiency of KGMHLBC is monotonic indicating that an exogenous variable's mean and variance of inefficiency can increase or decrease in the same way or in opposite directions (Wang, 2002). This also implies that the direction of the impact is monotonic which is determined by the sign of the δ coefficient. In other words, Wang's (2002) model assumes the marginal effect as non-monotonic which depends on the values of the exogenous variables while its impact on inefficiency can also change the direction of the inefficiency.

In this study, an airport's category is assumed to be constant which is similar with the model assumption of KGMHLBC. Where, in KGMHLBC, σ_{it}^2 is constant and $\gamma[k]=0$ for all k. Thus, marginal effects are equal to the slope of the coefficient $\sigma[k]$ multiplied by an adjustment function as shown in Equations (1.17) and (1.18). Similarly, in a model of constant σ_{it}^2 the effects of the variable on the conditional statistics are also monotonic. This is a simple model of marginal effects on $E\left(u_{it} / \hat{e}_{it} \right)$ which is similar to Equation (1.17) except μ_{it} and σ_{it} are replaced by μ_* and σ_* as:

$$(1.29) \quad \mu_* = \frac{\sigma_u^2 \mu_{it} - \sigma_{it}^2 (y_{it} - x_{it}\beta)}{\sigma_u^2 + \sigma_{it}^2}$$

$$(1.30) \quad \sigma_* = \frac{\sigma_u \sigma_{it}}{\sqrt{\sigma_u^2 + \sigma_{it}^2}}$$

By the same procedure it is also possible to obtain the marginal effects of $V\left(u_{it} / \hat{e}_{it} \right)$ from Equation (1.18).

Assumptions and hypothesis

Schmidt and Sickles' (1984) made an assumptions that a consistent estimation of $\hat{\sigma}_u^2$ requires the number of units N large to approach (N-∞). The generalized least squares (GLS) estimation results will be the strongest when N is large and T is small. Whereas if T is large and N is small, GLS or the random effects approach is useless and it is recommended that the within estimator be used as it exploits neither a distributional assumption nor the uncorrelatedness of the effects and regressors which do not allow time invariant regressors and also consistently estimate the intercepts for each firm. This argument is also proved using the Hausman test's results by testing random versus fixed effects models. Accordingly, the null hypothesis is strongly rejected which confirms that this study's model favors the fixed effects model (Stata output chi2(6) =33.1 and prob>chi2(6) =0.0000).

Taking Rashidghalam et al. (2016), Heshmati et al. (2016) and Kumbhakar et al. (2015) as basic references for the methodology and using a statistical software, this study also found separate inefficiency effects from the unobserved individual heterogeneity effects. More importantly, the models' examination for the separation of persistent inefficiency (time-invariant) and time-varying inefficiency (transitory) from unobservable individual effects was also done. In general, all performance measurement methods generated individual-specific effects. Thus, the time-variance of inefficiency effects and their separation from non-inefficiency heterogeneity effects are properly addressed.

This study hypothesized that both the output and input price variables are expected to have positive and significant effects in increasing the total cost of each airport. For instance, an increase in passenger movements as well as freight cargo transported increases demand for more airport facilities and infrastructure with associated higher costs. Similarly, with an ever-increasing devaluation/exchange rate, world oil prices and inflation, an input price will automatically increase which will also lead to cost hikes. In some cases, even though the output may decrease, input prices will not reduce and total costs follow input price trends. With increased access to road infrastructure, the demand for air transport will reduce as this and other modes of transport will be cheaper than air transport. Domestic cargo has reduced significantly in some airports while freight cargo at Addis Ababa Bole International Airport had an average growth rate of 18 percent.

5. Analysis and Discussion of the Estimation Results

This study used the stochastic cost frontier panel data approach for studying Ethiopian airports. Passengers and cargo freight transported were considered as outputs while price of labor, price of capital, and price of energy were the input costs. The analysis focused on the short-run and long-run cost efficiencies of Ethiopian airports. Time-invariant technical efficiency which is considered to be persistent technical efficiency on the one hand and time-varying technical inefficiency or transient technical efficiency on the other were separated and analyzed. Accordingly, in Table 1.4 the fixed effects estimation results are presented for the fixed effects model (Model 1), true fixed effects model (Model 2), and the KLH-2014 model (Model 3).

Table 1.4. Cost efficiency estimation results of FE, TFE and KLH models

Explanatory variables	Model 1 (FE)	Model 2 (TFE)	Model 3 (KLH)
Logarithm of total passenger movement in number (lnYp)	0.1027*** (0.06)	0.145*** (0.05)	0.134*** (0.06)
Logarithm of Cargo fright in kg lnYc	0.0054 (0.01)	0.005 (0.007)	0.007 (0.007)
Logarithm of price of labor (lnPL)	0.815*** (0.07)	0.814***(0.036)	0.801*** (0.06)
Logarithm of price of capital and fixed assets (lnPK)	-0.053 (0.11)	-0.082** (0.034)	-0.037 (0.042)
Logarithm of average world crude oil prices in Birr (lnPE)	-0.0144 (0.14)	0.156*** (0.05)	0.138** (0.04)
The time period (yr)	0.03 (0.03)	..	..
Dummies	..	Omitted	..
Constant	-42.52 (47.03)	10.7*** (0.50)	9.48*** (0.34)
R2 adjusted	89.88%	..	88.95%

Note: * p < 0.1, ** p<0.05, and ***p<0.01; standard errors in parenthesis.

Source: Authors calculations based on fixed effect, True fixed effect and KLH-2014 Model

5.1 Output and inputs price elasticities

The estimation results of the Cobb-Douglas cost model which comprises input prices, output, and technical change elasticities are reported in Table 1.4. In the fixed effects model (Model 1) estimation results of passenger output elasticity and price of labor elasticity are positive statistically significant. In the True fixed effect (model 2) all variables except freight cargo are statistically significant while in the KLH-2014 (model 3) passenger output, labour and energy was statistically significant. A 1 percentage point increase in passenger movement in each airport leads to a 0.1027 percent increase in the total airport costs other things remaining constant (FE). Similarly, the true fixed effects estimation has a positive and strongly significant impact so that a 1 percent increase in passenger output services leads to a 0.145 percent increase in the airport's total costs. The changes are low indicating an inelastic response by costs for output changes. In Kumbhakar et al.'s model (Model 3), a 1 percent change in passenger output services was highly associated with a 0.134 percent change in total airport costs on average during their study period. The parameter's estimates ($\beta_1 < 1$) show that in these models an airport's cost is inelastic to passenger output movements in all the airports studied. The cargo output's coefficients are not statistically significant suggesting airport costs are not responsive to changes in cargo output. The sum of the two output elasticities in all the three models is less than 1 suggesting that an airport's cost increases less than the output and there are increasing returns to scale.

Similarly, for every 1 percent increase in the price of labor the total cost of the airport increases on average by 0.815 percent in the fixed effects model (Model 1), 0.814 percent in the true fixed effects model (Model 2), and 0.801 percent in the KLH model (Model 3). Since the margin of error for the coefficient of the price of capital and fixed asset in the fixed effects and KLH-2014 model is higher than 0.10 percent, the airport's total costs are not much responsive to changes in the price of capital and fixed asset. In this model price of labor is the most determinant factor to increase cost expenditure, and total cost of the airport was much responsive to changes in the price of labor.

The third significant variable in this study as stipulated in the true fixed effects and KLH models is the price of energy. This shows that for every 1 percent change in the price of energy, the total cost of each airport increases on average by 0.156 percent and 0.138 percent for the models respectively. Since their values are less than 1, the total airport costs are price inelastic to energy price changes. The parameter of this variable for the fixed effects model is not highly responsive to changes in the price of energy.

In contrast to energy price elasticity, a 1 percent change in the price of capital PK, led to a reduction 0.082 percent in the airport's costs which is unexpected in the true fixed effects models. Even though an increase in capital is expected to increase cost outlay, since capital investment increase output and productivity of firms, this subsequently might reduce recurrent expenditure. The freight cargo output transported showed that the total cost of an airport was not responsive to changes in the freight cargo transported during the study period. Even though these results need further investigation, the trends in international cargo transported and its volume significantly increased over time while the domestic freight cargo declined significantly with an increase in access to road infrastructure. The coefficient of yr (0.03) implies that the margin of error for the coefficient of the time trend variable for the fixed effects model is positive but insignificant indicating the absence of cost saving technical progress at Ethiopian airports.

5.2 Efficiency of Airports

Efficiency levels of the studied airports are given in Table 1.5 which vary across time and among airports. In Table 1.5 short-run efficiency or transient efficiency is represented by the true fixed effects and KLH models while the long-run/persistent efficiency level is explained using the time-invariant persistent efficiency in the KLH model. Similarly, overall efficiency is also given by OTE of KLH models. The efficiency of fixed effects is also indicated for comparisons.

Table 1.5. Mean Cost Efficiency scores of airports (2002-17) (208 observations)

		Mean efficiency of each airport (in %)					
		Model 1	Model 2		Model 3		Model 4
ID	**Airports**	Fixed Effects (LR)	Efficiency of TFE (SR)	KLH-P (LR)	KLH-R (SR)	KLH OTE	BC-95 distance efficiency
1	AAB Int.Airport	3.0	61.0	4.0	85.0	3.0	5.60
2	Dire Dawa Intl Airport	13.3	70.8	16.0	86.0	14.0	11.18
3	Mekelle Intl Airport	16.6	75.7	20.0	86.0	17.0	15.34
4	B/Dar Intl Airport	16.9	74.2	20.0	86.0	17.0	15.17
5	Jimma domestic airport	25.4	74.0	28.0	86.0	24.0	15.02
6	Gonder domestic airport	23.7	73.8	27.0	86.0	23.0	20.33
7	Axum domestic airport	32.3	75.5	37.0	86.0	32.0	27.32
8	Lalibella dom. airport	48.2	67.0	54.0	85.0	46.0	41.62
9	Gambella dom. airport	65.6	76.5	71.0	84.0	60.0	45.13
10	Arbaminch dom. airport	45.2	64.9	48.0	86.0	41.0	23.80
11	Gode domestic airport	100	73.6	89.0	85.0	76.0	64.98
12	Assosa domestic airport	61.1	73.6	65.0	86.0	56.0	36.03
13	Jijiga domestic airport	73.0	63.8	77.0	85.0	66.0	52.52
Average		40.0	70.0	43.0	85.0	36.0	28.77

Source: Authors calculations based on fixed effect, True fixed effect and KLH-2014 Model

Based on an analysis of the fixed effects model, Gode Airport is a benchmarking cost efficient airport. whereas Jijiga and Gambella airports are at second and third place and Addis Ababa Bole International Airport, which is the national hub airport, Dire Dawa, Mekelle, and Bahir Dar international airports score 3 percent, 13 percent, and 17 percent respectively in cost efficiency. This shows that in the long-run the biggest Ethiopian airports will continue to be less cost efficient compared to smaller domestic airports. On the other hand, airports having more infrastructure, facilities, and services will continue to be inefficient compared to those having lesser facilities and services. The efficiency results also show that an airport can be efficient at the minimum services and facilities level. So, international airports are expected to maximize their cost saving strategies as compared to domestic airports. This is interpreted to mean that large international airports are expected to have large scales but are subject to unpredictable service demands leading to low cost efficiency.

Efficiency estimations based on the true fixed effects model focused on the short-run time-varying effects. The analysis implied that Gambella Domestic Airport had a 76.5 percent cost efficiency which was the highest, Mekelle International Airport had 75.7 percent cost efficiency and was at second place while Axum Domestic Airport with 75.5 percent cost efficiency was ranked the third efficient airport. Addis Ababa Bole International Airport, Jijiga Domestic Airport, and Arbaminch Domestic Airport had 61 percent, 63.8 percent, and 64.9 percent cost efficiency respectively. The highest cost efficiency at 76.5 percent was at Gambella Domestic Airport while the least cost-efficient airport was Addis Ababa Bole International Airport (61 percent) and the mean average time-varying efficiency levels of all the airports was about 70 percent. This shows that the average means actual costs of most Ethiopian airports according to the true fixed effects estimation was 30 percent higher than the minimum possible cost efficiency level.

The persistent efficiency KLH model is the other long-run indicative parameter. This model shows that Gode, Jijiga and Gambella had 89 percent, 77 percent, and 71 percent persistent efficiency respectively. This implies that in the long-run these airports will continue to be relatievely efficient, while Addis Ababa, Dire Dawa, Makelle, and Bahir Dar international airports had 4 percent, 16 percent, and 20 percent cost efficiency and will thus continue to be less efficient even in the long-run. This finding is the same as that for the fixed effects model in terms of airport types which are the relatievely best cost efficicnt and relatively least cost efficient with minor differences in the percentage of efficiency among the two models. Airports' cost efficiency levels in the short-run analysis ranged between 85 percent and 86 percent using the KLH model of residual or transient efficiency levels. This shows that most Ethiopian airports are relatively efficient in the short-run with 84 up to 86 percent level of transient efficicncy.

The overall cost efficiency in the KLH model showed that the relatively smaller airports such as Gode, Jijiga, Gambella, and Assosa scored more than 50 percent (76, 66, 60, and 56 percent respectively) in cost efficiency while other airports had scores less than 50 percent with Addis Ababa Bole International Airport being the least cost efficient scoring only 3 percent in efficiency. Based on the BC-95 distance approach the least cost efficient airport was Addis Ababa Bole International Airport (5.6 percent) while Gode Domestic Airport was the most cost efficient with a 64.98 percent efficiency level.

Table 1.6. Summary of airports' Cost efficiency using the fixed effects models (n=208) (in %)

Model	Efficiency component	Mean	Std. Dev.	Min	Max
Model 1	Efficiency of Fixed Effects	40.0	0.28	4.0	100.0
Model 2	Efficiency of True Fixed Effects (TFE)	70.0	0.18	22.7	96.7
Model 3a	Residual/Transient efficiency (KLH-R)	85.5	0.04	84.0	86.0
Model 3b	Persistent efficiency (KLH-P)	43.0	0.27	4.0	89.0
Model 3c	Overall technical efficiency (KLH-O)	36.0	0.23	3.0	76.0
Model 4	BC-95 distance efficiency	28.8	0.23	2.66	98.5

Source: Authors calculations based on fixed effect, True fixed effect and KLH-2014 Model

In summary, four efficiency effects models – the fixed effects model, true fixed effects model, Kumbhakar et al.'s (2014) model, and persistent and residual cost efficiency model -- were estimated and analyzed. Since their distributional assumptions varied with time and without time, the efficiency results also varied. Efficiency was estimated starting with the fixed effects model (Table 1.6). In the fixed effects model, the minimum cost efficiency during the study period was estimated at about 40 percent of the actual costs. This shows that on average actual cost of each airport exceeded the minimum cost by 60 percent. The range between minimum and maximum values showed the prevalence of extreme variations among airports in relative cost efficiency. The estimated minimum cost efficiency observed was 4 percent which is the lowest compared to the benchmark best performing airport scoring 100 percent efficiency. Hence, the actual costs of some airports exceeded the minimum costs by about 96 percent, though the time-invariant fixed effects model is strongly criticized for its distributional assumption in its inefficiency analysis as not being essential (the same is true for the random effects model too). Similarly, individual heterogeneity cannot be distinguished from inefficiency in both the fixed and random effects time-invariant inefficiency models.

To reduce some of the limitations of these models, Greene (2005a) developed the TFE model which was applied in this study and the estimation results are given in Table 1.6. TFE's efficiency was estimated to be approximately 70.0 percent on average. Its cost efficiency varied between 22.7 percent and 96.7 percent as transient efficiency. The true fixed effect approach is consistent with Filippini and Hunt's (2016) model applied for measuring interchangeably with TREM for transient energy efficiency and Mundlak's version of the random effects measure for persistent efficiency.

A separation of efficiency's components using Kumbhakar et al.'s (2014) model was also done. The KLH model's residual/transitory efficiency was estimated at 85.50 percent on average while persistent efficiency was estimated at 43.0 percent. Finally, the overall cost efficiency model KLH-2014's results showed 36.0 percent average efficiency ranging between 3.0 percent and 76.0 percent. The other model specified is the BC-95 distance efficiency estimation model which showed a mean efficiency of about 28.8 percent on average. As compared to the other specified models, KLH-2014 is relatively better for separating persistence and transitory efficiency rates. Based on the results obtained in model of KLH-2014, this study concludes that there is as an overall cost efficiency about 36 percent. Hence, on average the actual cost of each airport exceeded the minimum cost by 64 percent. The range of overall cost efficiency ranged between 3 percent and 76 percent showing the existence of large variations among airports' performance. Estimation of Battese and Coilli 1995 distance and Wang (2002) model has indicated in Table 1.7.

Table 1.7. BC-95 and Wang (2002) cost frontier inefficiency effects models (truncated-normal)

Logarithm of Cost Frontier	BC-95 distance function model 4			Wang (2002) marginal effect Model 5		
	Coeff.	Std. Err	z	Coeff.	Std. Err	z
Logarithm of Total passenger movement in number (lnYP)	0.323***	0.049	6.47	0.396***	0.029	13.62
Logarithm of cargo freight in kg lnYC	-0.0013	0.009	-0.15	-0.02**	0.008	2.49
Logarithm of price of labor (lnPL)	0.700***	0.035	19.7	0.606***	0.106	5.71
Logarithm of price of capital and fixed assets (lnPK)	-0.071	0.073	-0.98	-0.119**	0.054	-2.18
Logarithm of average world crude oil prices in Birr (lnPE)	0.3042	0.216	1.41	-0.333***	0.059	-5.62
Yr	0.065*	0.029	2.23			
Constant	-137.0	58.174	2.36	11.27***	0.529	21.28
Mu						
lnZ	0.385***	0.068	5.66	-0.359***	-0.049	-7.19
Constant	-1.456***	0.50	2.90	3.721***	0.511	7.28
Sigma_ U	0.555***	0.031	17.9	-	-	-
Sigma_ V	0.008	0.016	.47	-	-	-
Lambda	70.38***	0.0365	1928	-	-	-
Sigma_ U(lnZ)	-	-	-	-1.282***	0.226	-5.66
Average marginal effect on inefficiency E(U)				-0.3959		

Average marginal effect on inefficiency V(U)	-0.3118

Note: Log likelihood = -172.74, Prob>chi2 = 0.0000, Wald chi2 (6) = 871.46.

Technical elasticity

The elasticity of passenger and price of labor force in the BC-95 efficiency effects model were 0.21 and 0.77 respectively which were positive and statistically significant. The coefficient of technical change elasticity (yr) is 0.056 implying increasing costs over time by 5.6 percent per year for the same amount of services provided. In the BC-95 model capital and energy price elasticity are not statistically significant suggesting that cost is not responsive to a change in the price of capital and energy. In the Wang (2002) model elasticity of passengerand price of labor was 0.396, and 0.606 respectively while freight cargo, price of capital and price of energy was -0.02, -0.119 and -0.333 respectively. This shows that an increase in passenger volume and price of labor resulted in an increase in an airport's associated costs while an increase in the freight cargo, prices of capital and energy reduced an airport's related costs. The former result is as expected but the latter being negative is unexpected. Taking a total of elasticity's coefficients, 60 percent and 57 percent of the estimates with the BC-95 and Wang (2002) efficiency model respectively moved in the same direction with a price inelastic nature. This implies that as per the four variable estimations, Ethiopian airports function under a cost inelastic situation to price and output movement in each of the airports under consideration $(\beta_1 < 1)$ interpreted as decreasing returns to scale.

The coefficient of an airport's categories (Z) is positive with a highly significant sign implying that technical inefficiency levels will increase significantly on average by 38.5 percent every year across every airport considered. This is a serious and unexpected situation which demands attention for reducing airports' technical inefficiency. Since cost inefficiency effects are positive, this inefficiency will increase in the future. Hence, government interventions for bringing in structural changes at airports as cost saving strategies is very crucial and include a paradigm shift in cost saving in all the main cost centers such as infrastructure, airport facilities, and system installations for reducing both short-run and long-run cost inefficiencies.

The variance model's relationship is given by:

$\hat{\sigma}_s^2 = \sigma_u^2 + \sigma_v^2$ and $\hat{\gamma} = \sigma_u^2 / \sigma_s^2$

The square of sigma-u (0.2422) is 0.0586 and the square of sigma-v (0.4126) is 0.17027. The total of the square of the variance $\hat{\sigma}_s^2$ =0.2289. Following this functional relationship, the gamma variance parameter is $\hat{\gamma}$ =0.256. This measures the share of total variance attributed to cost.

The LR-test is computed using the restricted and unrestricted approach. Thus, LR= $\hat{\lambda}$ =-2[-172.74-(-139.457)] =-2(-33.283) =66.56.

Taken at the 1 percent level of significance, the calculated LR-test statistics are higher than the tabulated critical value of 5.412. Hence, the null hypothesis that there are no stochastic technical inefficiency effects is strongly rejected and this model confirms that technical cost inefficiency exists in the operations of Ethiopian airports during the study period.

Marginal effect of cost inefficiency

The variable airport category was also analyzed for its marginal effect on $E(u_{it})$ and $V(u_{it})$ to measure how an increase in an airport's basic facilities, services, and infrastructure changed the expected cost inefficiency and cost uncertainty respectively.

The coefficient of airport category for usingmas is -1.282 with a p-value equal to 0.000 and the coefficient of airport categories for mu is -0.3589 with a statistically significant p-value at 0.000. Thus, the statistical results show that the airports' categories in the model are supported by data.

The mean inefficiency value of marginal effects on the unconditional expectation of E(u) and the variance inefficiency value of V(u) are presented with constant airport category assumptions. The estimation results show that the marginal effect of E(u) and marginal effect of V(u) are both negative. This shows that increasing airport infrastructure, facilities, and systems reduces, on average, the level of cost inefficiency and the uncertainty of cost inefficiency. Specifically, for every 1 percentage increase in an airport's category, its cost inefficiency level reduces, on average, by 39.60 percent and uncertainty of cost inefficiency reduces by 31.18 percent.

6. Summary and Conclusions

Cost efficiency is a key concern for all firms. Previous efficiency analyses of airports mainly focus on the minimization of costs keeping quality and standard service provisions in their respective regions unchanged. This chapter examined cost efficiency of 13 Ethiopian airports covering the period 2002-17 using the stochastic cost frontier panel data approach. It also specified the Cobb-Douglas cost function where cost is a function of passenger output, freight cargo transported, price of labor, price of energy, price of fixed assets and price of long-run capital investments. It specified five models and estimated them for the analysis including the time-invariant fixed effects model, time-variant true fixed effects model, Kumbhakar et al.'s (2014) model, Battese and Coelli's (1995) efficiency effects model, and the marginal effect of inefficiency using Wang's (2002) model.

Based on the models, each airport's persistence and transient efficiency effects were identified. Cost implications of passenger output movements, price of a productive workforce, and price of energy, including the sum of price of fixed assets and price of long term capital investments were also examined. An econometric analysis of passenger movements per year and per airport and price of a labor productive workforce had the expected positive signs and were statistically significant in the five models. The price of energy was positive and strongly significant in the econometric analysis of true fixed effects and Kumbhakar et al.'s (2014) models. The sum of the two output cost elasticities is < 1 suggesting airport cost increases less than the output (increasing returns to scale). Airport cost was inelastic to change in passenger output and price of labour. Cost had insignificant responsive to changes in the freight cargo transported while other estimation results were not consistent across the models.

The efficiency results of this study of Ethiopian airports also show that time-invariant or long-run efficiency of the panel data model had a relatively low efficiency level with minor differences between efficiency of fixed effects (40 percent) and persistent efficiency of Kumbhakar et al.'s (2014) model (43 percent). The short-run/residual/transient efficiency levels had significant variations between the efficiency of true fixed effects (70.0 percent) and Kumbhakar et al.'s (2014) models (85.5 percent).

Airports efficiency levels showed that all international airports had lower cost efficiency compared to domestic airports. The biggest hub Addis Ababa Bole International Airport was the least efficient while the Gode Domestic Airport was the most efficient. This implies that airports which have minimum services and facilities or low infrastructure, have higher cost efficiency both in the short-run and long-run. Over all the possibility to be continue cost inefficient is very high in most airports. In the long-run, the biggest Ethiopian airports will continue to be less cost efficient compared to smaller airports. On the other hand, airports having more and better infrastructure, facilities, and services will continue to be inefficient compared to those having lesser infrastructure, facilities, and services. This implies that the size of infrastructure is larger than its efficiency scale.

The efficiency results also show that an airport can be efficient with minimum services and facilities. Though the short-run efficiency is a bit higher compared to the long-run efficiency, Ethiopian airports need to improve their efficiency levels in the short-term and develop long-term efficiency improvement strategies in both aeronautical and non-aeronautical areas. The management and concerned bodies at the airports should explore and optimize their current cost saving strategies as this is crucial for reducing costs and increasing profitability. More importantly, terminal and apron operations are expected to help make more efficiency gains. This implies that international airports should maximize their cost saving strategies compared to non-international/ domestic airports.

To sum up, Ethiopian airports have low levels of cost efficiency across airports and over time implying the need for developing standard infrastructure and expenditure provisions. This also calls for an expenditure analysis in terms of a cost benefit analysis for reducing costs beyond the production capacity. Similarly, expenditure and investments may need to consider passenger and freight cargo trends more than social and political equity goals and objectives. An airport having a higher level of infrastructure, facilities, and special airport systems has higher cost inefficiencies. Unless structural changes in cost savings are introduced, the positive cost inefficiency effects will continue to increase and might lead to inefficiency in total airport costs. Hence, strategic airport leadership is needed for structural changes for airports' revenue generation and cost reductions. In other word, Ethiopian airports should to improve the short-term cost efficiency and develop long-term efficiency improvement strategies. More importantly, a further assessment of operational as well as allocative efficiencies of all the airports is expected to promote cost efficiency.

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Chapter Three- Paper 2

An Analysis of the Production Efficiency of Ethiopian Airports

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Abstract

This study does an analysis of the efficiency of 13 domestic and international Ethiopian airports. It estimates the Cobb-Douglas production function using the panel data approach covering the period 2002-17. When estimating the production efficiency of these airports its focus is on the maximum attainable output of services that can be provided with the available inputs and technology. The efficiency levels can be measured using the ratio of actual output to maximum attainable potential output. Annual weighted average passengers served and freight cargo transported by each airport is treated as the dependent variable while labor, maintenance, repairing and operating expenses, and real capital investments are treated as the explanatory variables. The production model is estimated using several stochastic frontier approaches including the efficiency effects distance approach of Battese and Coelli (1995) model, fixed effect, separation of persistent and transitory efficiency of KLH-2014 (Kumbhakar et al., 2014), and MLE models. What is surprising about the findings is that many airports had very low levels of efficiency implying underutilization of the invested capital in the infrastructure. Besides, since persistent or long-run efficiency is very low, the problem of inefficiency will stay for a long period unless urgent measures are taken and implemented by the government for bringing about necessary structural changes. The negative and highly significant sign of the inefficiency of airport categories shows that an increase in airport production capacity will reduce their technical inefficiencies. This requires the airports' administration to focus on providing basic airport facilities in parallel with air traffic passenger growth including an airport master plan and developing a design for avoiding the underutilization of the facilities at the airports.

Keywords: production efficiency; persistent and transient efficiency; time-varying efficiency; time-invariant efficiency; airports; Ethiopia

JEL Classification Codes: C13; C14; C33; C51; D24

1. Introduction

The air transport industry started in the early 20th century after the first jet engine plane became operational in 1949. Since then the commercial air transport sector has grown more than 70 times. This shows rapid developments with significant and continuous technological improvements. Today the air transport industry is one of the most important industries in the world which transports humans and material goods. This sector makes significant contributions to productivity, economic growth, and social development of societies. Demand for this industry's services is very high due to its fast speed and safe transportation (Kocak, 2011).

Airports form a main component of the air transport industry and they can be defined as an airfield equipped with basic infrastructure having a control tower and passenger and cargo terminals for moving from the surface to air by allowing airlines to land and take off (Adler et al., 2013; Graham, 2018). An airport has a lot of infrastructure and facilities including runways, taxiways, aprons, gates, passenger and freight terminals, and ground transport activities. Airports also provide important aviation infrastructure for society and act as the drivers of contemporary economics' development. The contribution of air transport in general and airports in particular grows with the level of economic development of countries and the globalization of the world economy. Globally the airport industry is dominated by the advanced world. According to the Airport Council International (ACI, 2019), global air traffic reached 8.8 billion passengers and 122.7 million metric tons of cargo via about 100 million aircraft movements in 2018 with an annual passenger growth rate of 4.8 percent. Of the total passengers in 2018, airports in the Asia-Pacific region touched 3.3 billion passengers, European airports 2.4 billion passengers, North America 2 billion, and Latin America and Caribbean 651 million passengers. The Middle East had 396 million and Africa had 214 million passengers (ACI, 2019).

As compared to the world passenger volume, the Ethiopian air transport industry is in its infancy though it is among the leading ones by African standards. Relative to other African aviation industries, the sector in Ethiopia is contributing significantly to employment creation, revenue generation, foreign currency earnings, openness, and international relations. Besides, the Addis Ababa Bole International Airport is a hub for Central and Eastern Africa for transporting human and material goods. According to the Ethiopian Airlines Group, of the total passengers transported, more than 70 percent were transient/transfer passengers (EAG, 2017). Likewise, more than 80 percent of Ethiopian airports' revenue is generated from the state owned Ethiopian Airlines (henceforth, Ethiopian). Unlike airlines in other African countries which have suffered heavy economic losses, Ethiopian is growing fast (IATA, 2017) with an annual growth rate between 20 to 25 percent since 2005 (IATA, 2017).

This ever-growing sector can continue its growth in a sustainable way only if there is quality service provision that satisfies airlines and airports' customers. The aviation world is very competitive, that is, airlines, airports, roads, and railways are competing modes of transport so efficiency matters. During the last two decades, there has been a growing interest in measuring the efficiency and performance of airports. Ulku (2009) argues that airports have their own distinct characteristics in terms of technical, operational, environmental, and financial performance. Nevertheless, based on comparative studies, airports have been intensively and continuously subject to benchmarking analyses for ranking them according to their efficiency scores. Performance measurement analyses of airports can be done by considering airports as firms that use multiple inputs to produce multiple outputs in a complex production system. In an airport's production process, the well-known players are airlines, ground handling service providers, and terminal operators (Fernandes and Pacheco, 2007, and Ulku, 2009).

Increasing demand and competition in the aviation industry has forced airports to prioritize their technical and operational efficiencies. Benchmarking, performance targets and continuous improvements are a norm at airports. According to IATA (2011) failure to meet the minimum levels of performance result in a decrease in an airport's market share. Passengers play a pivotal role and customer information about the industry is becoming a global resource. Thus, integration along the entire length of the supply chain has become possible so that airlines, airports, retailers, tourism organizations, and the hospitality sector are able to tailor their products in line with passenger demands and expectations. This has not only improved service levels but also improved efficiency, boosting revenues, and decreasing costs for airports (Francis. et al. 2003, and IATA, 2017). These and other factors have triggered demand and resulted in competition for availing additional supplies in the form of expanding existing capacities at airports and adding new airports to the system. In doing so, all airports should be located near to air traffic market centers and be preferred by tourists, passengers, and airlines.

Though measuring airports' efficiency is very crucial, such a scientific study of airports has not been done in Ethiopia. Application of the stochastic frontier approach to the airport industry and to African airports is a unique research contribution (of this dissertation) and a better understanding of the importance of airports. To the best of my knowledge, an airport specific stochastic frontier panel data approach is very rarely studied. This research also contributes to the limited number of airport specific studies and can be helpful as an input for policymaking for the Ethiopian aviation industry in terms of efficient utilization of existing airports, meeting the demands for airport expansion, and future capacity investments.

The main objective of this study is to examine the output determinants of Ethiopian airports, gaining a proper understanding of the technical efficiency of Ethiopian airports over time and separating efficiency between short-run and long-run effects which may be useful for policymaking. The aviation industry is extremely sensitive to competition and to minimum standards. This implies that with ever increasing demand and strong competition among airports, an efficiency analysis becomes very crucial. On the other hand, fulfilling international standards of services is becoming a mandatory requirement. Without efficiency, survival and facing competition will be extremely difficult for airports in many parts of the world. Among many factors, an airport's production efficiency is the most important determinant and relevant factor for sustaining its long-term competitiveness by attracting airlines and passengers. Hence, the need and importance of measuring the efficiency of Ethiopian airports is unquestionable.

The level of efficiency is measured following different parametric approaches for specific airports. Taking Ethiopian airports as a production unit, the main objective of this research is analyzing the production efficiency of Ethiopian airports and investigating their inefficiencies using different model specifications. This includes decomposing technical efficiency into persistent and transitory/residual inefficiency components. This can provide lessons in further enhancing airports' performance.

Research with such characteristics is rarely done and thus this study can serve as a lesson.

This study identifies the level of efficiency through time-invariant and individual specific efficiency effects using the fixed-effects model as an introduction. Then, it separates persistent inefficiency and time-varying inefficiency from unobservable individual effects with an advanced model developed by Kumbhakar et al., (2014) and the maximum likelihood estimation (MLE) method. Finally, the distance function frontier model using Battese and Coelli's (1995) model are estimated for analyzing the effects of Ethiopian airports' technical inefficiency.

The findings of this study vary across models and distributional assumptions underlying the models chosen. Even though the study has a limited number of observations, its findings show that most Ethiopian airports have low technical efficiency levels which call for the need for developing competitive strategies that can attract more air traffic and generate greater revenues for airports. Government interventions for structural changes are critical. The efficiency analysis in this study concentrates on airports' overall financial, labor force, and physical outputs. Based on its results this study recommends a more detailed and thorough investigation of the strengths and weaknesses of physical, technical, operational, and financial efficiency analyses.

The rest of this chapter is organized as follows. Section 1 gives a general introduction while Section 2 provides a brief introduction to the Ethiopian aviation industry and its growth performance in terms of revenue, passengers, aircraft movements, and freight cargo transported. Section 3 does a review of literature on the stochastic frontier function and its application to the aviation industry. Section 4 gives a description of the data and the model's specification and presents the details of the estimation procedures used in the study. Section 5 estimates and discusses the results. Section 6 provides a summary and the conclusion.

2. The Aviation Industry in Ethiopia

The aviation industry in Ethiopia has been a successful sector in Africa for more than seven decades. The Ethiopian Civil Aviation Authority and Ethiopian were established in 1945 and 1946 respectively. Ethiopian, despite working in poor national economic conditions, has been leading the African aviation industry for years. It has been a success despite a poor economy suffering from an acute civil war, famines, and following a socialist economic policy. *Economist* (1989)[5] praised Ethiopian as being an 'unqualified success'.

Oqubay and Tesfachew (2019) reviewed the key Ethiopian pathway and technological transformation practices to see how nations learn and catch up the 'late latecomer'. They pin point out that Ethiopian is working with leading global competitors, a strong sense of commitment to the Ethiopian nationality that grew in intensity, and a vision oriented implementation of a strategic planning framework helped and Ethiopian continued to work on its technological capability development, additional skill formation, aggressive new market development, and commitment to Pan-Africanism. These are some of the key factors in the success of the aviation industry in Ethiopia in the last seven decades (Oqubay and Tesfachew, 2019). According to these authors, Ethiopian continue expanding and upgrading to recent aviation technologies and improving its organizational and managerial capabilities helped it to reduce its gap with advanced leading global aviation industries.

In addition, Ethiopian airports have also played a significant role in the success of the airlines. Bitzan and James (2016) argue that improvements in an airport's efficiency enhance the productivity of the airline industry and also directly contribute to regional development. The aviation industry in Ethiopia has created direct employment for about 16,000 employees. Ethiopian had a real revenue of 0.04 percent of GDP in 2016 (Table 2.1).

Table 2.1. Growth trends in national GDP (2011=100 base year prices) and the Ethiopian Airline Group's (EAG) revenue (in million Birr)

Year	Real Gross Domestic Product GDP	Real Gross Domestic Product Growth	Ethiopian Airlines Group's Real Revenue	Percentage Share EAG Real Revenue to RGDP
2010	455,268.5	10.6	209.642	0.05
2011	515,078.5	11.4	256.252	0.05
2012	559,621.6	8.7	258.591	0.05
2013	618,842.2	9.9	280.474	0.05
2014	682,454.2	10.3	307.538	0.05

[5] https://www.economist.com/gulliver/2018/09/11/ethiopian-airlines-is-founding-new-african-flag-carriers

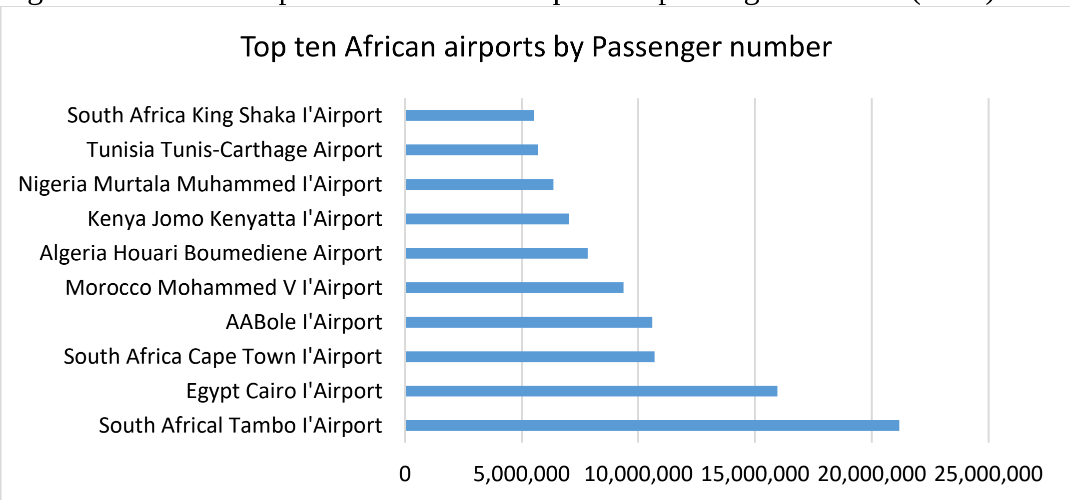
2015	748,021.1	10.4	306.921	0.04
2016	807,862.7	8.0	308.755	0.04

Source: The National Bank of Ethiopia (NBE) and the Ethiopian Airline Group's annual report (2017).

The Ethiopia aviation industry's share in the Ethiopian GDP during the last six years ranged between 0.05-0.04 percent (real GDP to annual operating revenue) while taking real operating revenue, on average, the share of the airline industry to real GDP was about 0.5 percent. According to the National Bank of Ethiopia's annual report (2018), the annual share of transport and communication was 10.1 percent, 10.1 percent, 10.2 percent, 10.7 percent, and 12.5 percent respectively during the period 2013-17 (NBE, 2018).

The top ten African airports are presented in Figure 2.1 which shows that the top ten Africa airports transported more than 5 million (the least) passengers per year. The leading African airports in total passenger numbers by the end of 2017 were South Africa Tambo International Airport with 21,180,060 passengers followed by Cairo International Airport with 15,959,076 passengers, and Cape Town International Airport with 10,693,063 passengers. The Addis Ababa Bole International Airport served more than 10,600,000 passengers in 2017.

Figure 2.1. African top ten international airports in passenger numbers (2017)



Source: Author's calculations based on the ACI database (2018).

Though developing countries' airports have low passenger volumes compared to airports in advanced countries, developing countries recorded a higher percentage of growth rate (around 8.3 percent) (ACI, 2019). This implies developing countries have high growth potential in the future subject to their economic development. As shown in Figure 2.1, countries with better economic conditions such as South Africa and Egypt had a higher number of passengers compared to countries with lower economic development. This is also manifested in the revenue generating capacity and service provision segments.

Table 2.2. Average revenue generated during the study period (at 2011 constant prices)

ID (Airports)	Mean (000)	Std. Dev. (000)	Minimum (000)	Maximum (000)	CV
Addis Ababa I'nal airport	648,000.00	508,000.00	108,000.00	1,710,000.00	0.78
Dire Dawa I'nal airport	26,700.00	70,800.00	4,113.94	292,000.00	2.65
Mekelle I'nal airport	7,602.21	7,430.02	339.82	22,300.00	0.98
Bahri-Dar I'nal airport	5,500.77	5,055.50	995.46	15,900.00	0.92
Jimma domestic airport	4,453.00	7,015.75	149.84	19,300.00	1.58
Gonder domestic airport	4,408.18	3,611.94	207.87	11,200.00	0.82
Axum domestic airport	3,538.15	2,857.99	227.97	9,068.16	0.81
Lalibella domestic airport	3,021.62	2,385.57	158.59	7,091.89	0.79
Gambella domestic airport	5,678.21	8,928.02	6.50	22,900.00	1.57
Arbaminch domestic airport	944.02	808.59	94.56	2,287.73	0.86
Gode domestic airport	1,034.84	784.88	84.43	2,111.21	0.76
Assosa domestic airport	1,319.55	2,318.39	2.43	9,360.09	1.76
Jijiga domestic airport	2,139.85	2,202.37	22.08	6,145.12	1.03
Total	54,900.00	220,000.00	6.50	1,710,000.00	4.01

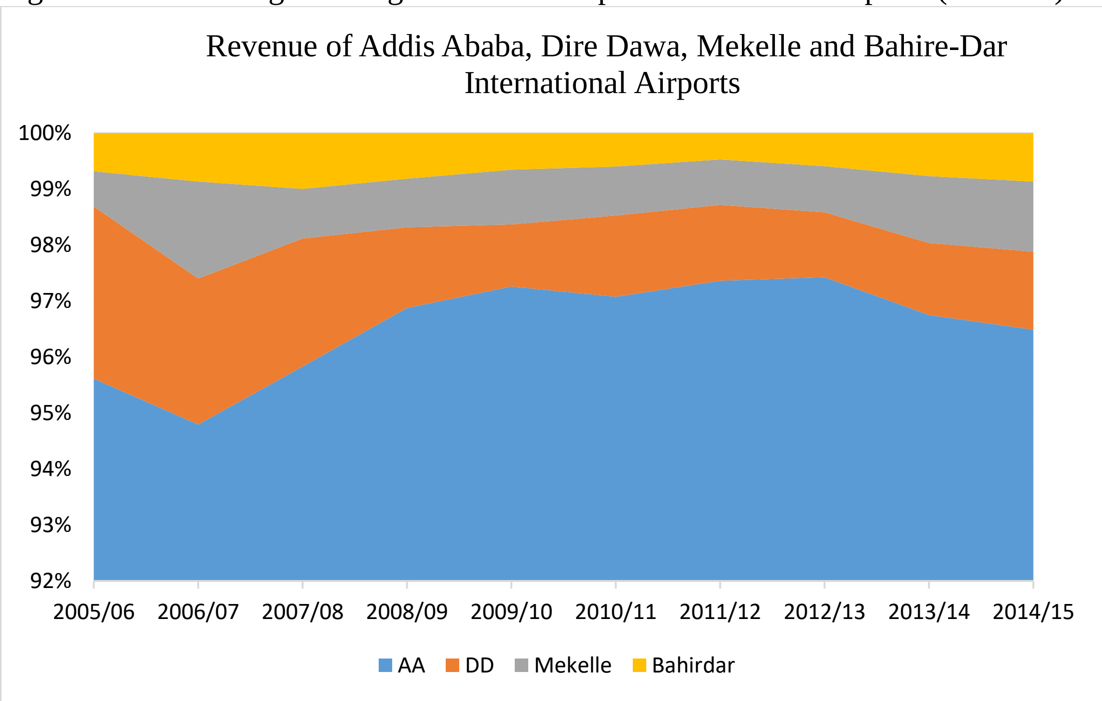
Note: CV=StdDev/Mean.

Source: Author's calculations based on Ethiopian Airports (2018).

Airports' average income generating capacity as shown in Table 2.2 is very low for almost all airports except Addis Ababa International Airport which had the maximum income of 1.7 billion ETB per year and an average mean revenue for all the 16 years of the study period at about 648 million ETB. Dire Dawa International Airport was the second, and Mekelle International Airport the third highest revenue generating airports. Revenues generated by other airports ranged between 1 to 5 million ETB. On average, the lowest mean revenue (less than 1 million ETB) was by Arbaminch domestic airport while Gode and Assosa domestic airports were the second and third lowest revenue generators during the study period. This minimum revenue generating trend shows that airports such as Assosa, Gambella, Jijiga, Gode, and Arbaminch had very low revenue generation capacities for some time and this is also an indication of the underutilization of the infrastructure and facilities at these airports.

As shown in Figure 2.2, the highest aeronautical and non-aeronautical revenue was collected by Addis Ababa Bole International (AABI) Airport while the three remaining international airports were the second, third, and fourth highest revenue generating airports. This shows that except AABI the other airports had very low revenue generating capacities. Since economic activities in Ethiopian airports are limited to peak hours, their main sources of revenue were aeronautical activities and not non-aeronautical sources.

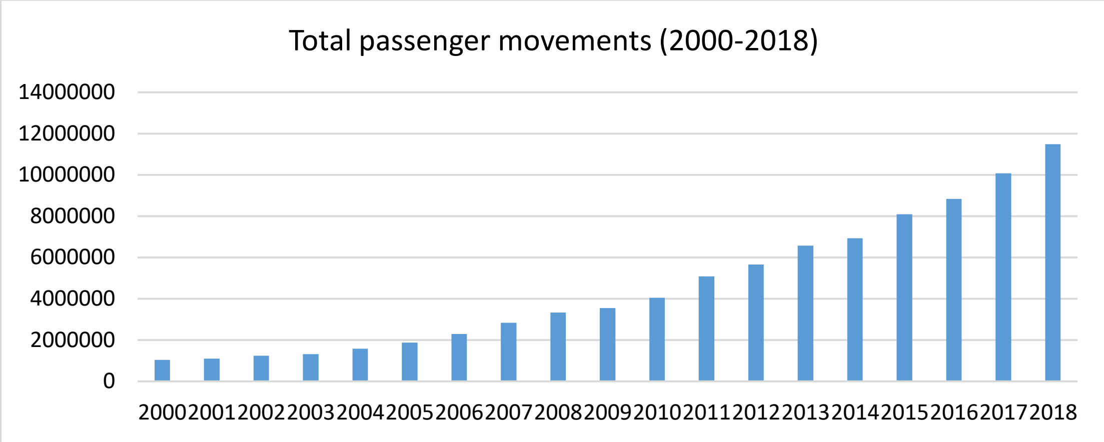
Figure 2.2. Revenue generating trends at Ethiopian international airports (2006-15)



Source: Author's calculations using data from Ethiopian Airports (2019).

As a result, airports' revenue sources mainly focused on passenger services and charging the aircraft using the airports. By the end of 2018, the air transport market in Ethiopia had reached more than 11.5 million passengers and was dominated by AABI which is the largest and busiest airport in East Africa. In 2010, this airport serviced about 4 million passengers while in 2018 this number had grown to 11.5 million passengers per annum. This shows that in less than one-decade demand for air transport grew three-fold (nearly 187 percent growth). The growth trends in domestic and international passengers transported during 18 years (2000-18) are given in Figure 2.3.

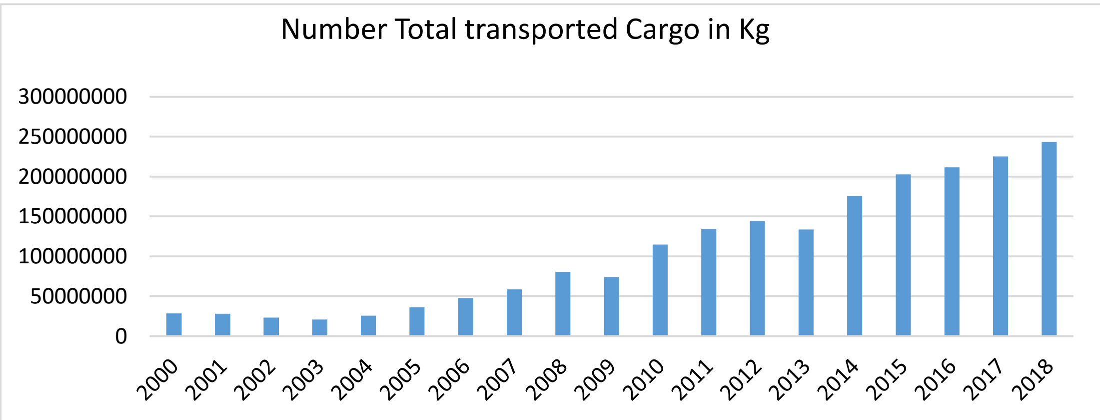
Figure 2.3. Total number of passenger movements per year (2000-18)



Source: Author's calculations based on data from Ethiopian Airports (2019).

Addis Ababa is the capital of Ethiopia and the headquarters of the Africa Union. In addition, it also has many diplomatic as well as international organizations based there. Economic growth accompanied by a huge population size led to this rise in demand for air transport. Increase in demand is likely to continue in the near future as well. Further, Ethiopia is at the center of the globe (Far East and US/South America as well as South Africa and Europe). Its geographic location is advantageous for the country's airlines and airports even though they face strong competition from regional and continental airports.

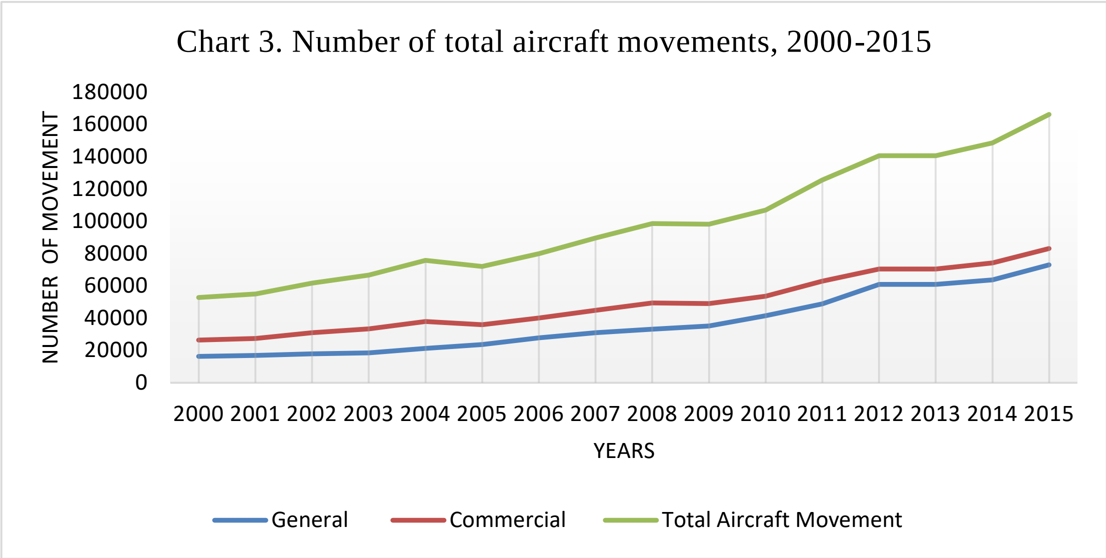
Figure 2.4. Total cargo transported per year (in kg) (2000-18)



Source: Author's calculations based on data from Ethiopian Airports (2019).

Like the growth in overall air transport, the volume of cargo transported has increased since 2005 with minor fluctuations in 2009 and 2013. Figure 2.4 shows that the overall cargo volume was growing continuously. Accordingly, the annual growth reached about 240 million kg per year in 2018. Many charter flights and commercial aircraft frequently land and take off from AABI. The growth trends in passenger numbers (domestic and international) as well as aircraft movements (commercial and non-commercial) for 15 years (2000-15) are given in Figure 2.5.

Figure 2.5. Total number of aircraft movements per year (2000-15)



Source: Author's calculations based on data from Ethiopian Airports (2018).

3. Literature review

3.1 Stochastic frontier functions

This research evaluates the efficiency of Ethiopian airports. Developing the stochastic production frontier model follows the theoretical foundation in literature. Fried et al. (2008) and Hjalmarsson et al. (1996) are among the studies that explain that technical efficiency can be estimated using a stochastic frontier analysis (SFA) and a data envelopment analysis (DEA). They explained the methodological approach of SF and DEA that the stochastic frontier (SF) focuses on the parametric approach assuming the existence of a separate inefficiencies and random errors while DEA is a non-parametric approach that only considers inefficiency. In the frontier production function, deterministic and stochastic production functions are both parametric methods of measuring efficiency.

In a stochastic frontier analysis, the basic concept is measuring and improving the level of firms' efficiency of service and production. Economics uses the terms efficiency and productivity interchangeably. Production function defines the relationship between output and a set of inputs and their quantities. The production frontier also defines the same thing in terms of the relationship but specifically represents the maximum output attainable from each input level. Coelli et al. (2005), Filippini and Hunt (2015), Heshmati (2003, 2013), Heshmati and Kim (2016), and Kumbhakar and Lovell (2000) explain and define these terms. Productivity is derived from the production function as the ratio of output to input level. Hence, the higher the output the better the productivity. Efficiency, on the other hand, is defined based on a feasible production set and is a combination of all feasible sets of input-output production frontier relationships.

In literature, technical efficiency is defined as the ratio of observed output to the maximum feasible output. Heshmati (2013), Heshmati and Kim (2016), Kumbhakar (1988), and Kumbhakar and Lovell (2000), discuss the frontier production function and the concept of technical inefficiency defined as the amount by which the actual output falls short of the maximum possible output that sets the frontier. The following is the summarized empirical development of frontier production model and its basic assumptions since the 1970s.

3.1.1 General production frontier model

Work on stochastic frontiers started in the 1970s by Aigner and Chu (1968), Aigner et al. (1977), Meeusen and van Den Broeck, (1977), Kumbhakar (1988, 1990), Battese and Coelli (1995), and Heshmati and Kumbhakar (1995). They reviewed the ordinary least squares (OLS) regression production function that fits the OLS function through the center of the data and assumes homogeneity, that is, all firms are efficient. The second is a deterministic production frontier that fits a frontier function over the data assuming there is no data noise. Finally, SFA production frontiers are a 'mix' of these two functions.

Accordingly, the general stochastic production frontier model can be written as:

(2.1) $\ln y_j = f(\ln x) + v_j - u_j$

where y_j is the output produced by firm j, x is a vector of the explanatory variables, v_j is the stochastic error term (white noise), and u_j is the one-sided error term that represents the technical inefficiency of firm j. Both terms (v_j and u_j) are assumed to satisfy the assumption of independent and identical distribution (I.I.D.) with constant variances σ_v^2 and σ_u^2 respectively.

Having a deterministic frontier, the production of each firm j is written as:

(2.2) $\ln \hat{y}_j = f(\ln x) - u_j$

where following the neoclassical average production function (that is, no inefficiency) the efficiency level of production can be defined as:

(2.3) $\ln y_j^* = f(\ln x)$

3.1.2 Functional form of the scholastic production frontier

The choice and selection of the functional form depends on the data type and applicability of the method. Some functional forms that are frequently used are Cobb-Douglas, constant elasticity of substitution (CES), Translog, Generalized Leontief, and Normalized quadratic forms. Afriat (1972), Coelli et al. (2005) and Kumbhakar and Lovell (2000), explain that the translog functional form is a flexible and preferable functional form which can be applied to many empirical studies. Despite being simple, the Cobb-Douglas functional model is also a preferable functional model though it is restrictive to the presence of a model error.

The Cobb-Douglas production function can be written as:

(2.4) $\ln y_j = \beta_0 + \sum_i \beta_j \ln x_{ji} + v_j - u_j$

According to this functional form, the Cobb-Douglas production function assumes that the elasticity of substitution has constant values. A value of one implies that the production elasticity of all inputs remains constant. A 1 percent proportional change in the input level will produce the same percentage change in output, irrespective of any other change in the function.

3.1.3 Stochastic production frontier model with panel data

According to Heshmati (2013), Kumbhakar and Heshmati (1995), and Kumbhakar et al. (2014), the general setup of a panel data stochastic frontier model with several inputs and one output (which is linear in parameter) can be written in the form of:

(2.5) $\ln y_{it} = x'_{it}\beta + v_{it} - u_{it}$

This is identical to the model in (2.4) except the subscript "t" that is added to represent time period. In panel data modeling some of the strong distributional assumptions of the cross-sectional model about inefficiency and noise effects are relaxed to disentangle their separate effects so the prediction of the technical inefficiency becomes more consistent and we are able to examine changes in technical efficiency over time. Schmidt (1976) argues that the independence assumption is unrealistic despite its convenience for estimation.

A firm's technical efficiency can be defined as the ratio of the observed output y_{it} to the maximum feasible output $y_{\max}$ in conducive environmental conditions given the same time period and inputs used by the firm (Coelli et al., 2005, p. 275).

Mathematically, technical efficiency can be reformulated as:

(2.6) $TE_{it} = \frac{y_{it}}{y_{\max}} = \frac{\exp f(x_{j,it};\beta_{it}) * \exp(v_{it}) * \exp(-u_{it})}{\exp f(x_{j,it};\beta_{it}) * \exp(v_{it})} = \exp(-u_{it})$

This analysis shows that the measure of technical efficiency lies between the value of zero and one (Coelli et al., 2005).

Once the parameters of the production model are estimated using the ML, JLMS type of estimation techniques, conditional mean can be used for estimating firm-specific inefficiency which can be found by:

(2.7) $TE_{it} = E[\exp(-u_{it}) / \exp(v_{it} - u_{it})]$

hence, v_{it} is a symmetric disturbance random error/statistical noise which includes uncontrollable factors like weather and other environmental conditions, functional form approximation errors, omission of relevant inputs, and measurement errors (Bezat, 2009, 2011; Coelli et al., 2005).

By construction the term u_{it} is a non-negative random variable related to technical inefficiency which lies between 0 and 1. If it is one, the firm is technically efficient and if it is less than one, the firm is technically inefficient. This implies that when $TE_{it} < 1$ an observed output is less than the maximum feasible output. Such a condition is characterized by $\exp(v_{it})$, which allows for random variations across producers. Accordingly, technical efficiency is defined as the ratio of 'observed actual' or 'realized output' to the maximum possible stochastic frontier output (Bezat 2009, 2011; Coelli et al., 2005).

3.2 Applications to the aviation industry

The literature review mainly focuses on a study of the stochastic production frontier and a little on the data envelopment analysis in general and the air transport sector throughout the world in particular. The empirical findings of some of the prominent scholars in the area of stochastic frontier production are now discussed.

Productivity, effectiveness, and efficiency are the most important concepts in performance measurements. In many cases, the terms efficiency and productivity are used interchangeably, even though their meaning is not identical. Many authors explain the words productivity, effectiveness, and efficiency by giving similar meanings and interpretations to them (Heshmati and Kim, 2016; Liebert, 2011; Liebert and Niemeier, 2010; Ulku, 2009). Efficiency and productivity focus on a relative analysis depending on the concept of maximum attainable outputs. Heshmati (2013) defines productivity as the ratio of some function of output(s) for some function of input(s) while efficiency is considering the maximum output which can be produced with available inputs. Efficiency can be measured either by transforming inputs into the production function using the available production technology and/or by constructing a sample of production units using the inputs and outputs from the sample for the maximum attainable output. Once the maximum attainable output is calculated and determined then efficiency can be measured by the ratio of actual output to maximum attainable output.

The concept of efficiency (Zarraga, 2008) has been interpreted using both economic and technological perspectives. Economic efficiency is a combined effect of all feasible resources that can be obtained with the lowest possible production cost per unit of output while technological efficiency depends on the maximum possible amount of outputs subject to scarce resources as output oriented or input oriented approaches. That is, the minimum amount of resources used for producing and determining the level of production. In addition, an overall technical efficiency measure (Zarraga, 2008) can be classified either as pure technical efficiency or scale efficiency though technical efficiency depends on the type of returns to scale. On the other hand, scale efficiency is the ratio of the overall technical efficiency to pure technical efficiency. It shows managerial ability to choose the optimum amount of resources among the possible range available for obtaining a pre-determined maximum achievable production level. Hence, technical returns to scale can be used for measuring an airport's managerial performance (Zarraga, 2008).

The major efficiency factors that are beyond managerial control are airport size (scale of aggregate output), average aircraft size using the airport, share of international traffic, share of air cargo traffic, extent of capacity shortage/congestion, delays, connecting/transfer ratio, and the nature of the airport, that is, how far it is from alternative modes of transport, tourist centers, and population conditions. These factors are used for addressing the means of the analysis. Fried et al. 2008 also argues that in principle, the residual can be attributed to the differences in production technology, differences in the scale of operations, differences in operating efficiency, and differences in the operating environment wherever the production process occurs. In the absence of reliable and valid measurement techniques, measuring performance is difficult. The service industry is more problematic compared to the manufacturing industry since it includes service quality and customer satisfaction (Kocak, 2011).

Gillen and Lall (1997) and Hooper and Hensher (1997) were the first to come up with ground-breaking analyses of airports' efficiency and productivity in their articles with DEA and index-based TFP for US and Australian airports respectively. Subsequently many other studies significantly improved the performance assessment of airports including airports' heterogeneous character. They assumed heterogeneous production and/or cost functions in parametric studies or conducted second stage analyses to explain the inefficiencies of the DEA estimates. In addition, some studies discovered that airports' performance was overstated without including undesirable outputs and hence they included them directly in the model (Gillen, 2011, Gillen and Lall, 2001, Liebert and Niemeier, 2010).

Currently, the aviation industry is becoming more competitive. Hence, practitioners and researches have become concerned about the productivity of airport investments. This has resulted in airports using various benchmarking analyses for increasing their productivity using scarce resources. They use passenger traffic, aircraft movements, cargo throughput, and financial ratios as key indicators for assessing their performance. Input-output relationships have also been developed which are used as benchmarks for competition and better performance of the airport industry system.

Airports produce multiple outputs using multiple inputs. Airports production processes are segmented and each segment has a qualitatively different approach (Ulku, 2009). Airports provide facilities and services for generating revenue besides fulfilling their social responsibility. The main revenue sources for an airport encompass aeronautical and non-aeronautical sources. Aeronautical revenue sources are associated with core aviation activities of runways, aircraft parking, ground handling, and terminals' check-in, security, passport control, and gate operations. There are also aircraft landing fees, aircraft parking and taxiway charges, and passenger terminal and facility charges. The other revenue sources are non-aeronautical activities within terminals and on airport land including terminal concessions such duty-free shops, restaurants, advertising, and entertainment facilities. There are also ground transport, property rentals, and other income from various activities on the airport's territory (Graham, 2018; Ulku, 2009). The ratio of aeronautical revenue to non-aeronautical revenue varies greatly depending on the type of airport (Ulku, 2009) such as an international hub, low cost carrier or tourist attracting airport, and passenger profile as well as the competitiveness of the airport. Hence, airport efficiency is seen as integrating capacity and utilization of all aeronautical and non-aeronautical services.

Pathomsiri et al. (2006) studied 56 US airports (between 2000 and 2003) for comparing airports' efficiency and performance under different scenarios. They explain that efficient airports were assumed to be congested and busy despite some externalities such as delays and noise effects. These were undesirable outputs observed during the process and were also expected to increase with the volume of traffic at the airports. A relative analysis and comparison was done on the frequency of aircraft movements per runway and aircraft delays per passenger runway for those airports which had more than one runway. The authors found that airports with higher density of traffic were associated with higher average delays. Hence, airport efficiency at the cost of more delays may be seen as undesirable output by airport regulators, the civil aviation authority, airlines, and passengers. This forces airports to measure productivity and operational efficiency including all desirable and undesirable outputs.

Pathomsiri et al. (2006) applied a directional output distance function model to assess the airports' operational efficiency. They considered three physical inputs (land area, number of runways, and area of runways) as well as three desirable outputs (passengers, number of on-time flights, and cargo throughput), and two undesirable outputs (delayed flights and time delays). Their study showed that measuring airports' efficiency varied depending on the number of desirable and undesirable outputs considered. For instance, instead of full analysis, the analysis can only consider a partial process for desirable outputs and/or the regulatory body's policy perspective and politics considered as undesirable outputs when measuring the productivity and overall efficiency of airports. These authors concluded that in the absence of undesirable outputs, the most congested airport could be efficient and congestion could be either because the airport is busy with its existing slots or is facing expansion constraints. Despite delayed flights and time, there were non-busy and smaller airports identified as being efficient (Pathomsiri et al., 2006).

Gillen and Lall (1997) used the data envelopment analysis for 21 US airports over the period 1989-93 for measuring their performance using a multiple output and multiple input approach in the second stage using Tobit regression while environmental, structural, and managerial variables were included as control variables in the model. They found that the 'net' performance index and the variable manager had some control over the airports' performance. Tsekeris (2011) evaluated the performance of Greek airports using technical efficiency and he found that seasonality mattered in an airport's performance. Besides, the location, size, and operating characteristics increased the technical efficiency of Greek airports.

Though performance measures can be total or partial, the commonly practiced and easily managed type of study is done using partial measures of airport efficiency (Liebert and Niemeier, 2010). However, partial measures are misleading and require an interpretation of the analysis. Liebert and Niemeier (2010) explained in their critical assessment, taking the undesirable outputs as one scenario of the total measurement, annual growth in passengers, aircraft movements, and cargo throughput could potentially increase an airport's efficiency by 23 percent, 20 percent, and 35 percent while a partial measure which ignores the undesirable outputs showed a 139 percent, 91 percent, and 364 percent growth in passengers, aircraft movements, and cargo throughput respectively.

In their efficiency and performance analysis as well as its interpretation, Liebert and Niemeier (2010) maintain that having a busy or congested airport does not necessarily guarantee an efficient airport, unless airports are expected to maintain quality services by reducing delays to the lower possible level even when handling sufficiently high passenger traffic volumes. They further explain that estimating the maximum possible production output can be compared and justified using more sophisticated methods such as DEA, SFA, and the price-based index approaches in general and for airport production technology in particular. Besides, the total measure of airport performance requires a complete set of inputs and outputs that need to carefully consider the airport's operating environment since inefficiencies happen not only because there is management inefficiency but also be due to the operating environment. Any limitation during the proper scanning of the environment may prevent conclusive findings about the effects of management, regulation, competition or size effect on an airport's performance.

Since the use of the airport related distance function inefficiency literature is very limited, Coelli and Perelman (1999, 2000) provide a multi-input and multi-output approach which is directly related to a multi-factor approach for studying airports. Considering the challenges of single and multi-output production functions, Coelli and Perelman (2000a) developed the multi-output/multi-input technology approach. This approach uses the distance function as a solution to the multi-output problem taking data for European railways. The distance function could be compared with an estimate of the production function that involves aggregate output measures. Despite the variations in output-oriented, input-oriented, and constant returns to scale, distance functions were estimated using the corrected ordinary least squares (COLS) method. A comparison of the production function having a Tornqvist output index revealed lower aggregation bias in relation to revenues in the production function measure of aggregate output (Coelli and Perelman, 2000b).

A multi-output distance function using linear programming of DEA, COLS, input-oriented and constant returns to scale (CRS) distance function were estimated and compared by Coelli and Perelman (1999). A strong degree of correlation between the three input and output-orientated results was obtained using alternative estimation methods. The correlation of parametric linear programming and COLS was the strongest. The authors concluded that the combined technical efficiency score obtained using input-output orientated, constant returns to scale were the preferred set of scores for the distance function (Coelli and Perelman, 1999).

Coelli and Perelman (2000a) explained the performance of multi-output industrial production in terms of technical efficiency and its usefulness were measured by comparing multi-output industries' production. They argue distance function was considered as part of the comparison of technical efficiency, though its behavioral assumption was not applicable to cost minimization or profit maximization principles.

In the technical efficiency study of European Railways, the average estimated result obtained using COLS was 0.863 which ranged between 0.980 and 0.784 for Netherlands and Italy respectively (Coelli and Perelman, 2000). There was a substantial difference in the ranking parameter's estimates and technical efficiency which raised doubts about the reliability of a single output model in aggregating the total revenue measure as proxy output aggregate (Coelli and Perelman, 2000b).

Airports also have strategic importance in connecting and integrating other services. Airports can bring greater wealth, provide substantial employment opportunities, and encourage economic development which can be a lifeline for isolated communities. They have a very significant effect both on the environment in which they are located and on the quality of life of the residents living nearby. Growing awareness about general environmental issues has heightened environmental concerns about airports (Graham, 2013). Ferro et al. (2010) analyzed the relative environmental efficiency of Argentinean airports. Their study focused on regional differences with variables such as metropolitan, tourist destinations, and provinces. Based on a DEA analysis, they found that there were significant differences in the airports' efficiency. Their best practice also showed that a majority of Argentinean airports were operated at high levels of efficiency. Using the DEA approach, the returns to scale were found where some large airports had decreasing returns to scale while the small airports had increasing returns to scale.

Ferro et al. (2010) concluded that the scale dimension should be decreased if there are decreasing returns to scale while the inverse is true for increasing scales and the dimension constant returns to scale (CRS) is adequate in these cases. For airports which have increasing returns to scale (IRS), they recommend additional investments for increasing the size of the airports for gaining greater efficiency.

Fageda and Voltes-Dorta (2012) considered airport specific financial and traffic data from around the world for a sample based composite non-standard profit function approach for estimating Spanish airports' cost and revenue efficiencies. They found that losses in small airports were a result of Spain's revenue inefficiency which was partly explained by a rigid system of aeronautical revenues and an inadequate promotion of retail activities. They further showed that in Spain, airports with less than 500,000 passengers would likely incur financial losses due to individual management problems at the airports which is common in most European and North American countries. The authors emphasize the importance of separating aeronautical and non-aeronautical revenue because disaggregation according to their analysis, improved the characterization of the role of managerial factors (the impact of ownership or price regulation on specific airports' aeronautical revenue efficiency).

Lai et al. (2015) discuss the multi-criteria decision-making method for 24 major international airports. Their empirical analysis labelled the analytic hierarchy process (AHP) incorporating the weightings of input and output variables into the DEA and assurance region (DEA-AR) model. Their findings show the existence of a discriminatory power in the proposed AHP/DEA-AR model is more than the basic DEA model while measuring the efficiency of airports. They concluded that subjective judgment in the AHP approach brought a new perspective to airport efficiency and provided researchers an opportunity for developing their results following reflective perceptions. Their findings contributed to benchmarking activities, to debating on privatization, other varying perspectives, and influencing the viewpoint of grading airports.

Based on their analysis, they recommend that the approaches' applicability for policymakers and practitioners was more effective compared to operational efficiency pf airports, and therefore they will be able to take well-informed decisions. Lai et al. (2015) allowed the AHP/DEA-AR approach for getting well-defined ranking scales. Their approach also allowed them to prioritize the measurement according to their perspective. They concluded that multiple comparisons following the approach using panel data with a diverse nature of stakeholder opinions may bring better insights. Po-Lin et al. (2015) studied a multi-criteria decision making method using analytic hierarchy process, DEA and assurance region DEA (DEA-AR) model. In their study 24 major international airports considered and found that the AHP/DEA-AR model is better than the basic DEA model.

Examining the efficiency of 40 Turkish domestic airports during 2008 using the DEA approach, Koçak (2011) considered the variables operational expenses, number of personnel, flight traffic, and number of passengers as the input variables and number of passengers/area, flight traffic/ runways, and total load as output variables. The most efficient airports were identified using the DEA solver methodology. Ulku (2009) studied German airports using the data envelopment analysis to assess their relative efficiency. He also studied the efficiency levels and other influencing factors besides doing relative assessments throughout the world except in Africa. The findings of the global analysis showed that under the CRS model on average, Asian and American airports were the most efficient while European airports came next followed by Latin American airports.

Management issues faced by airport operators have been a major focus area of airport performance studies. The performance of these operators varies considerably depending on their ownership, management structure and style, degree of autonomy, and funding. Under most circumstances the actual airport operators provide only a small proportion of an airport's facilities and services while most of them are provided by airlines, handling agents, government bodies, concessionaries, and other specialist organizations. The mechanism by which operators choose to provide a diverse range of airport facilities has a major impact on their performance and on their relationship with their customers (Graham, 2013).

Airport operators need to have a unique identity to have overall control and responsibility of airports. Each airport operator faces the challenging task of coordinating all the services to enable the airport system to work efficiently. The service providers are one of the airport's stakeholders which operators need to consider while considering other shareholders including airport users, employees, local residents, environmental lobbyists, and government bodies. A complex situation exists with many of these groups having different interests and possibly holding conflicting views about airports' strategic roles. All the stakeholder relationships are important but, clearly, developing a good relationship with the airlines is critical as ultimately this will largely determine the air services on offer at the airports (Graham 2013, 2014).

In general, a few studies on efficiency measurement in relation to stochastic frontier as well as data envelopment analyses were reviewed in this section. A summary of studies and their findings covered in this review is given in Table 2.3.

Table 2.3. Summary of key airport performance studies reviewed

Studies on airport efficiency using DEA/distance functions					
Paper/Authors	Sample	Model /theory	Estimation method	Input(s)/Output(s) Variables	Key findings
Po-Lin et al. (2015)	24 major international airports	Multi-criteria decision making method. Analytic hierarchy process	DEA and Assurance Region DEA (DEA-AR) model	Inputs: employees, gates, runways, size of terminal area, length of runway. Outputs: passengers, ATM, freight and mail, and total revenue.	The AHP/DEA-AR model is better than the basic DEA model
Kim (2015)	11 major airports in the Asia-Pacific region in 2001 and 2013	The DEA model (super-SBM) panel data	Super-efficiency slack-based model is a non-radial model	Employees, area of passenger and cargo terminals, labor costs, depreciation as input variables. Output variables: passengers, cargo, and total revenue	Market in the region is led by China and its neighbors. There were also efficiency improvements
Gillen and Lall (1997)	21 top airports in the US during 1989-93	Panel of 21 US airports	DEA (second stage Tobit regression)	Multiple outputs which airports produce and multiple inputs which they use	Terminal efficiency improved by increasing gates
Tsekeris (2011)	39 international and domestic Greek airports	Cross-sectional data for 2007	DEA approach (CRS and VRS)	Outputs: passenger, cargo and ATM. Inputs: runways, terminal and parking area and operating hours	IRS seasonal efficiency, airports with more tourists
Pathomsiri et al. (2006)	56 major US airports	Directional output distance function model	The partial process and policy perspective or politics	Inputs: land and terminal area, runways, and labor units. Outputs: passengers, non-delayed ATM, cargo, desirable and undesirable ATM	the most congested and could be efficient

Source: Compiled by the author.

4. Data and Model Specifications

4.1 Dataset and a description of the variables

This study used the stochastic frontier panel data approach for 13 international and domestic airports. The data was obtained from annual records of Ethiopian Airports (EA). Based on balanced panel data, 208 observations were done for the analysis covering the period 2002-17. The production frontiers were fitted for a single aggregate output (composite index of total national passenger movements and cargo transported) and three inputs (capital investments, maintenance expenses, and labor working hours). The inputs and outputs are identified and described in Tables 2.4 and 2.5.

Table 2.4. Summary Statistics of monetary output/input data (2002-17), (NT= 208 observations, constant values in 2011 prices)

Variable	Descriptions (constant price)	Mean (000)	Std. Dev. (000)	Minimum	Maximum (000)	CV
RTR	Real total revenue of the airport (ETB)	54,900	20,000	6,505	1,710,000	4.01
Y1b	Total passenger movement times service charge (ETB)	116,000	508,000	35,633	3,560,000	4.38
RTC	Real total cost of the airport (ETB)	6,003	13,100	36,982	65,300	7.00
K	Real net capital investment of each airport (ETB)	287,000	679,000	3,728,077	4,720,000	9.00
M	Real maintenance and repairing and other operating expenses (ETB)	3,465	10,700	3,085	84,700	7.00
RWSE	Real wages and salaries as HR expenses (ETB)	2,787	4,487	37,988	29,500	7.00

Source: Author's calculations based on data from Ethiopian Airports (2018).

The description can also be provided as follows: The input variable of interest is real net capital (RNK) investment. The capital investments are the foundation of the airport. During the study period, the minimum investment was about 3.7 million ETB while the maximum investment was about 4.7 billion ETB. Long term capital investments include the investment costs for the terminal building (passenger and cargo), runways, taxiways, and apron construction including installation and provision of complementary facilities such as a power house and a large warehouse for storing perishable goods that need to be transported.

In this research, long term capital investments are those that have a lifespan of more than 20 years. According to Table 2.4 some airports were operating with minimum investments and incomplete facilities whereas some others were equipped with all necessary airport facilities. The interesting point in Table 2.4 is that the capacity of some airports had the minimum value per annum. In terms of revenue the minimum for one specific year was 6,505 ETB, the minimum maintenance and repairing costs were 3,085 ETB, and the minimum total costs of an airport were 36,982 ETB. This shows that some airports were underutilized and their revenue was not able to cover their recurrent budgets.

The other input variable of interest is real maintenance and repairing costs including other operating expenses except salaries and wages. The minimum and maximum costs are given in Table 2.4.

Table 2.5. Summary Statistics of physical output/input data (2002-17), (NT= 208 observations)

Variable	Descriptions	Mean (000)	Std. Dev. (000)	Minimum	Maximum (000)	CV
Y1	Total passenger movement for each airport	233.135	708.774	1,197	5,107.7	3.04
Z2	Aircraft movement	6.896	16.656	222	111.202	2.42
Yc	Total freight cargo transported (kg)	11,400	40,400	1	243,000	3.53
Y1c	Total passenger movement converted to 100kg	40,900	143,000	119,700	1,020,000	3.49
Y	Aggregate sum of total passenger movement and freight cargo in kg	52,300	178,000	120,691	1,260,000	3.40
L	Man-day productive hours of EA employee	96.188	139.75	5,040	756	1.00

Source: Author’s calculations based on data from Ethiopian Airports (2018).

Table 2.5 focuses on airports’ physical outputs. Trends in passenger movement ranged between a maximum of 5.11 million passengers per annum to a minimum of 11,197 passengers per annum. Similarly, aircraft movements ranged between 111 million as the maximum and 222 per year as the lowest. In Ethiopia, airports’ output variables can be listed as passenger numbers transported from departure/origin to destination areas. Movement of aircraft is related to transporting passengers and goods and services. Finally, the revenue generated from various aeronautical and non-aeronautical services should also be accounted for.

As can be seen in Table 2.5 the dependent variable is Y which is an aggregated sum of total annual passenger movements converted into weighted values in kg and annual air freight cargo transported as cargo. One person including his luggage is approximately equivalent to 100 kg of air freight cargo. Measuring the work load unit is an aggregate of passengers with luggage imposing the same costs on airport infrastructure as 100 kg of cargo. Martín and Voltes-Dorta (2011) state that based on Doganis' (1992) work such a weighted sum is more logical for airlines than airports since it directly effects aircraft payloads and the same weight of passengers and freight may not require similar physical and financial input resources.

Y1 is annual passenger movements in number, Z2 is aircraft movements at each airport, and L is the man-day productive hours of each worker. An effective working hour is calculated as the actual number of workers multiplied by annual working hours excluding weekends and annual leave.

With regard to data quality assurances, all financial data are reviewed and approved by the federal auditor general every year. Any discrepancy is corrected and consistency and accuracy of the data is also checked. On the other hand, statistical data for passenger/cargo and aircraft movements is recognized by the Airport Council International (ACI). Hence, service related data for this research was reported to the Airport Council International and the International Civil Aviation Organization on a monthly basis.The hypothesized expected signs of all the three input variables (capital, maintenance, and wages) are positive and having a significant effect on increasing the aggregated sum of passenger and air freight cargo movements in each airport every year.

4.2 Model specification framework

This study was conducted based on the stochastic production frontier panel data model. It applied a modified version of Aigner et al.'s (1977) model. This is a parametric estimation in the panel data approach of a time-varying and time-invariant stochastic frontier analysis. The functional form of the stochastic frontier is determined by testing the Cobb-Douglas production function relative to the less restrictive translog form of the production function. For a small sample of observations, the Cobb-Douglas or the generalized Cobb-Douglas method is preferred to the translog functional form. The likelihood ratio test of the Cobb-Douglas model against the translog flexible functional form was conducted and based on the available data and its methodological applicability, the model fit the Cobb-Douglas production function.

The next step specifying the estimation technique in the panel data analysis was between the fixed-effects versus random-effects models. The Hausman fixed-effects versus random-effects models' test results were in favor of the fixed-effects model. Hence, the fixed-effects approach was an appropriate estimation technique as compared to the random-effects model that best represents the Cobb-Douglas production function. This study mainly focused on separating persistent time-invariant technical inefficiency and transitory time-varying inefficiency following Kumbhakar and Heshmati (1995), Heshmati (2013), and Kumbhakar et al.'s (2014) models.

A production function is a function that summarizes the changing and mapping of inputs into outputs. These can be physical outputs or service outputs. In this study, an airport service output, which takes the form of passenger movements, is regarded as output and can be obtained by using the inputs airport infrastructure including physical capital, human capital, and other operating and maintenance costs.

The production function can be mathematically formulated in the form:

(2.8) $Y = f(K, L, M)$

where Y is the weighted sum of annual domestic/international passengers and freight cargo in kg is the output workload unit, L is airport workers' annual man-day productive hours excluding annual leave, weekends, and holidays, M and K are real values of maintenance and repairing, and other operating expenses and values of annual long-term net capital investments after depreciation at constant prices respectively. The explanatory variable *year* is a trend representing technology and shift in the production function over time.

In the stochastic production function, an efficiency analysis using a panel dataset can be written as:

$$(2.9)\ Y_{it} = f(K_{it}, L_{it}, M_{it}; \beta)\exp(\varepsilon_{it})$$

The model allows for decomposing the deviation from the production frontier into the statistical noise and inefficiency, that is, $\varepsilon_{it} = v_{it} - u_{it}$. This can be shown in the log form of the stochastic panel data model of the Cobb-Douglas production function specified as:

$$(2.10)\quad \ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln M_{it} + v_{it} - u_{it}$$

In these equations, $\ln Y_{it}$ is the logarithm of output and the other three independent input variables are $\ln K_{it}$, $\ln L_{it}$ and $\ln M_{it}$ representing logarithms of net capital investments, man-day productive hours while maintenance and repairing, and other operating expenses are inputs of production respectively. Output $\ln Y_{it}$ is measured as the weighted sum of the total number of passengers and freight cargo serviced by every airport annually. The input variables $\ln M_{it}$ and $\ln K_{it}$ are maintenance and repairing capital goods, other office operational expenses and long-term net capital investments respectively. These are measured in aggregate and converted into constant values in 2011's ETB prices; $\ln L_{it}$ is the total number of individuals in the workforce per man-day productive hours (excluding annual leave and public holidays).

Estimation techniques and procedure presented in Kumbhakar and Heshmati (1995), Kumbhakar et al. (2015), and Rashidghalam et al. (2016) successfully separated the persistent inefficiency (time-invariant) component and the time-varying inefficiency (transitory) component from unobservable individual heterogeneity effects. Generally, all performance measurement methods are expected to produce individual-specific effects which are heterogeneous and not necessarily inefficiency effects. Thus, in line with the studies discussed in the literature review and using their approaches in studying Ethiopian airports, the time-variance of inefficiency effects and their separation from non-inefficiency heterogeneity effects are addressed in five models. These are now presented along with the different models' underlying assumptions.

Model 1: Time-invariant fixed-effects technical inefficiency

In this model, the estimated inefficiency is time-invariant but individual-specific. It is important to note that technical efficiencies remain constant over time. In other words, it is also assumed that estimation is possible without many strong distributional assumptions. As stated by Kumbhakar et al. (2014), Parmeter and Kumbhakar (2014), Rashidghalam et al. (2016), and Kumbhakar et al. (2017) the essence of the analysis is the specific unobservable individual effects of the panel data that forms the base for measuring inefficiency. Taking the assumptions into account, the panel data time-invariant stochastic frontier model can be written as:

(2.11) $\ln Y_{it} = f(K_{it}, L_{it}, M_{it}; \beta) + \varepsilon_{it}$

$$\varepsilon_{it} = v_{it} - u_{it},\ u_{it} \geq 0,\ i = 1,...,N; t = 1,...T$$

where $f(K_{it}, L_{it}, M_{it}; \beta)$ is a linear function of the explanatory variables, log of input quantities in a Cobb-Douglas production function model, and $u_{it} \geq 0$ is time-invariant technical inefficiency of individual airport i. In this part, u_{it} is considered as the basic feature of the panel data model which is specific to an individual airport and remains constant throughout the time under consideration.

The stochastic frontier panel data model with time-invariant inefficiency has been estimated with no distributional assumptions in literature. According to Schmidt and Sickles (1984) this model can be analyzed by assuming either that u_i is a fixed parameter or a random variable for the fixed-effects model and/or for the random-effects model respectively. Selection of the model depends on the degree of relationship between inefficiency and the covariates of the model. In the context of the standard panel data model the framework of the fixed-effects model can be applied if correlation is allowed between the explanatory variable and inefficiency whereas in the case of the random-effects model no correlation is assumed between u_i and $f(K_{it}, L_{it}, M_{it}; \beta)$.

With the exception of individual effects which are one sided, the model in Equation (2.11) is considered as a one-way error component model which is similar to other broadly addressed panel data models. This helps in having a simple transformation and interpreting the transformed individual effects as constant inefficiency which never changes over time (Kumbhakar et al., 2015; Parmeter and Kumbhakar, 2014; Kumbhakar et al., 2017; and Rashidghalam et al., 2016). According to Parmeter and Kumbhakar (2014) this idea is the opposite of pure firm heterogeneity. Parmeter and Kumbhakar (2014) and Kumbhakar et al. (2015) explain that the time-invariant inefficiency model be it a fixed-effects or a random-effects model does not consider separating inefficiency from individual heterogeneity.

The fixed-effects framework

The fixed-effects model was first proposed by Schmidt and Sickles (1984). Assuming a Cobb-Douglas production function form, in a fixed-effects model $f(.)$ is a linear function of the inputs' explanatory variables. The time-invariant inefficiency panel data SF model is written as:

(2.12) $\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln M_{it} + year_i + v_{it} - u_i$

$$\ln Y_{it} = (\beta_0 - u_i) + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln M_{it} + year_i + v_{it}$$

(2.13) $\ln Y_{it} = \alpha_i + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln M_{it} + year_i + v_{it}$

where $\alpha_i = \beta_0 - u_i$ so, u_i and including α_i , i=1,…, N are assumed to be fixed parameters that will be estimated along with the parameter vector β . α_i is also allowed to have an arbitrary correlation with the explanatory variables. According to Schmidt and Sickles (1984) Equation (2.13) is similar to the standard FE panel data estimation model. They applied this by using the standard estimation methods for estimating the parameter of the model. As explained by Parmeter and Kumbhakar (2014) the standard FE panel model can provide consistent estimates of β though $\hat{\alpha}_i$ is a biased estimator of u_i and $u_i > 0$ by construction and hence α_i is treated as fixed and unobserved individual effects in the model.

The assumption of the fixed-effects model is that the inefficiency terms u_i is freely allowed to correlate with x_{it} (the regressors). Mundlak (1961) maintains that inefficiency is correlated with the inputs and are considered desirable properties of empirical applications in such models. To avoid perfect multi-collinearity with α_i , the FE approach excludes other time-invariant regressors such as region from the list of explanatory variables x_{it} (Kumbhakar et al., 2015; Parmeter and Kumbhakar 2014).

This model is estimated using OLS by including individual dummies as regressors for α_i which we call the least squares dummy variable (LSDV) method where the coefficients of the dummies are estimates of α_i. Each individual firm's cross-sectional unit has one fixed effect parameter and the number of dummies to be included in the model is equal to the number of cross-sectional units in the data. Thus, N+K+1 parameters are estimated. N is the number of cross-sectional units, K is the number of slope coefficients of regressors x_{it} variables, and 1 is the overall intercept.

The difficulties in this model can be managed using different techniques before removing α_i. As mentioned by Kumbhakar et al. (2014,), Kumbhakar et al. (2015) and Parmeter and Kumbhakar (2014) the best approach in a panel data model is first difference and/or within transformation that helps to eliminate α_i and the transformed model can be estimated using OLS. Hence, the OLS estimator of $\hat{\beta}$ is a consistent estimator for β in which the values of $\hat{\alpha}_i$ are recovered from the residual mean of each individual cross-sectional unit $\hat{\alpha}_i = \bar{y}_i - x_i'\hat{\beta}$. Once $\hat{\alpha}_i$ is obtained, a simple transformation can be used for recovering $\hat{u}_i > 0$ which will also will be a consistent estimator if $T \to \infty$. Parmeter and Kumbhakar (2014) and Kumbhakar et al. (2017) further elaborate that in a panel data time-invariant model consistent estimates of β can be obtained through the transformed model as $T \to \infty$. This implies $\hat{u}_i$ is estimated based on Schmidt and Sickles (1984) model as:

(2.14) $\hat{u}_i = \hat{\alpha}_i - \min_i\{\hat{\alpha}_i\} > 0$, $i = 1,...,N$

The implicit assumption in this model's formulation is that the most efficient firm/unit in the sample is considered to be 100 percent efficient and the inefficiency estimate in this fixed-effects model is relative to the best firm/unit in the sample. So, firm specific efficiency can be estimated from:

(2.15) $\hat{T}E_i = \exp(-\hat{u}_i)$ $i = 1,...,N$

According to Rashidghalam et al. (2016) the only limitation of this FE model is its sensitivity to the most efficient observations serving as the reference frontier, a strong assumption of time-invariant inefficiency, is that individual heterogeneity and inefficiency not being separated.

Model 2: Separating persistent and time-variant transitory inefficiency effects

The previous stochastic frontier panel data model assumed technical inefficiency to be individual-specific but time-invariant. Hence, the inefficiency levels may vary across individuals, but be constant over time. The implications of the model are also explained (Kumbhakar et al., 2015; Parmeter and Kumbhakar, 2014) as inefficient units which do not change over time meaning that the units do not learn over time. Such an inefficiency condition may be considered a result of managerial incapability. A firm's management will not change during the period of the study considering the fixed effect panel data model assumption whereas in the current globalization such conditions are unrealistic and in reality, changes are expected over time.

Alternative models have been developed and advanced which assume that inefficiency changes over time. Time-varying inefficiency effects models are more general than time-invariant inefficiency effects models. This has helped time-varying models to accommodate various situations of inefficiency. Parmeter and Kumbhakar (2014) further explain that time-invariant models are mostly viewed as special cases of time-varying models. Time-varying models can be classified into many categories, four of which are highlighted as follows:

First, distribution free approaches that include the model developed by the Cornwell et al. (1990) and the model developed by Lee and Schmidt (1993). Their models of inefficiency focus on the deterministic and random components with distributional assumptions.

Second, distributional assumptions related to the deterministic and stochastic components of time-varying inefficiency. In this approach, models developed by Kumbhakar (1990), Battese and Coelli (1992), and Kumbhakar and Wang (2005) are used.

The third model separates firm heterogeneity from inefficiency. This model was developed by Greene (2005a, 2005b) to distinguish individual heterogeneity from inefficiency through true random and fixed-effects approaches.

Finally, more decomposition of the model is done in Equations (2.16) and (2.17) that separate firm effects, persistent inefficiency, and time varying inefficiency components.

Kumbhakar et al. (2014) and Colombi et al.'s (2014) models

As stated by Kumbhakar et al. (2015), the alternative multistep model faced a problem in treating specific firm-effects as persistent inefficiency which may yield an upward bias in inefficiency effects. Some other models exclude firm-effects from inefficiency that yields downward biases in the estimates of overall inefficiency. Hence, Kumbhakar et al. (2017) explain that all panel data models developed so far do not properly address the general model introduced about separation of inefficiency effects. Thus, the assumption was not fully satisfactory and the way of estimating the full panel data SF model was not clear. The models developed by Colombi et al. (2014) and Kumbhakar et al. (2014) introduced better solutions for overcoming some of the limitations of the previous models. They embrace the structure of four components of inherent weaknesses with the general panel data model. In their models, the error term is split into four components to take into account different factors effecting output given the inputs. Kumbhakar et al. (2015,) and Kumbhakar et al. (2017) explain the four components model as follows. The first component captures firms' latent heterogeneity (Greene 2005a, 2005b), which has to be separated from inefficiency effects; the second component captures short-run or time-varying inefficiency; the third component captures time-invariant persistent inefficiency; and the last component captures random shocks (Heshmati et al., 2018). If the first component is used for capturing persistent inefficiency, the model is reduced to Kumbhakar and Heshmati's model (1995) or the alternative multistep approach.

According to Kumbhakar et al. (2014) and Colombi et al. (2014), the model is specified as:

(2.16) $Y_{it} = \alpha_0 + f(K_{it}, L_{it}, M_{it}; \beta) + \mu_i + v_{it} - \eta_i - u_{it}$ where, $\eta_i > 0$ and $u_i > 0$ are the two inefficiency parts, μ_i and v_{it} are also two non-inefficiency parts (firm-specific heterogeneity effects and noise components). Accordingly, the embraced and inherent four components appeared in their work for the first time while other authors' models applied them in various combinations but not all of them at the same time.

As compared to previous models, the improvements in this model have been discussed by Heshmati et al. (2018), Kumbhakar et al. (2015) and Kumbhakar et al. (2017) in several ways:

1. If some of the time-varying inefficiency models can accommodate firm effects, they may fail to take into account the possible presence of permanent (that is, time-invariant) effects on a firm's inefficiency which are called persistent/time-invariant components of inefficiency.
2. The time-varying inefficiency stochastic frontier model considers a firm's inefficiency effects at time *t* is as independent of its previous level inefficiency effects. Since η_i is a time-invariant component and u_{it} is a time-varying component, it makes more sense for firms to remove some of short-run rigidities of inefficiency η_i, though some other inefficiencies can stay with the firm over time, that is, u_{it}.
3. A significant number of SF panel data models were not accounting for the simultaneously of the effects of unobserved firm heterogeneity on output, though they considered time-invariant inefficiency. Thus, these models also had problems in separating time-invariant/persistent inefficiency and firm effect heterogeneity.

In general, the model proposed on the decomposition of error terms was mentioned by Kumbhakar et al. (2015,) and Kumbhakar et al. (2017). Hence, the error term in the production function can be decomposed into three main components: a firm-specific time-varying inefficiency term; firm-specific effect capturing latent heterogeneity; and a time- and firm-varying random error term. The problem is that firm heterogeneity arises at the cost of ignoring long-term or persistent inefficiency. This implies that long-term inefficiency is also confused with latent heterogeneity.

Equation (2.16) considered a single stage ML method with distributional assumptions for the four components. Here, Kumbhakar et al. (2014), Kumbhakar et al. (2015) and Kumbhakar et al. (2017) considered a simpler multi-step procedure. Hence, the model in (2.16) can be rewritten as:

(2.17) $Y_{it} = \alpha_0^* + f(K_{it}, L_{it}, M_{it}; \beta) + \alpha_i + \varepsilon_{it}$

where $\alpha_0^* = \alpha_0 - E(\eta) - E(u_{it})$; $\alpha_i = \mu - \eta_i + E(\eta)$ and $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$.

Having mentioned this specification, the values of α_i and ε_{it} have zero mean and constant variance random variables and Equation (2.17) can be estimated in three steps:

- In the first step, estimating β using the standard fixed-effects panel regression approach. The estimated value of Equation (2.17) that predicted the values of α_i and ε_{it} is represented by $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$. The second step estimated from step one (time-varying technical inefficiency u_{it}) is estimated using the predicted values of $\hat{\varepsilon}_{it}$.
- The second step's model specification is:

(2.18) $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$

Where v_{it} is i.i.d. $N^+[0, \sigma_v^2]$, u_{it} is i.i.d $N^+[\mu, \sigma_u^2]$ that produces $E(u_{it}) = \sqrt{(2/\pi)\sigma_u}$ which implies that in any two or more procedures, ignoring the difference between the true and predicted values of ε_{it} is a common practice. Hence, Equation (2.18) can be estimated using the standard SF technique. As Kumbhakar et al. (2015) referring to Jondrow et al. (1982) maintain this process and produced a prediction of the time-varying residual technical inefficiency components, $\hat{u}_{it}$.

- In the third step, the final approach of estimating Equation (2.17) is done in term η_i. This model applies the same procedure as in step two and estimates the model using the best linear predictor of α_i from step one as:

(2.19) $\alpha_i = \mu - \eta_i + E(\eta)$

where μ_i is assuming i.i.d. $N^+[0, \sigma_\mu^2]$, and η_i is i.i.d. $N^+[0, \sigma_\eta^2]$, means that $E(\eta_i) = \sqrt{(2/\pi)\sigma_\eta}$

Equation (2.17) can be estimated following a cross-sectional approach using the standard normal–half-normal SF model. Kumbhakar et al. (2015) referring to Jondrow et al.'s (1982) procedure followed it as a base for estimating the persistent technical inefficiency component η_i. Here, persistent technical efficiency can be estimated from $PTE = \exp(-\eta_i)$ where η_i is the JLMS estimator of η_i; the product of persistent and residual efficiency results have an overall technical efficiency of: $OTE = PTExRTE$.

Model 3: The Maximum Likelihood Estimation (MLE) model

The maximum likelihood (ML) model can be estimated by imposing distributional assumptions on the terms v_{it} and u_{it} like in Pitt and Lee (1981) model. This model can be written as:

$$
\begin{aligned}
& Y_{it} = f(K_{it}, L_{it}, M_{it}; \beta) + \varepsilon_{it} \\
(2.20) \quad & \varepsilon_{it} = v_{it} + u_{it} \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_{it} \sim N(0, \sigma_u^2)
\end{aligned}
$$

Kumbhakar et al. (2015), Filippini and Greene (2016), and Rashidghalam et al. (2016) underlined that a repetition of the procedure enabled the ML estimation method to produce a higher efficiency in its estimation by providing strong assumptions of the normality of the random error term. According to their analysis the likelihood function for the i th observation can be given as:

$$(2.21) \quad \ln L_k = cons + \ln \Phi(\frac{\mu_{k^*}}{\sigma_*}) + \frac{1}{2}\left\{\frac{\sum_t \varepsilon_{it}^2}{\sigma_v^2} + \left(\frac{\mu}{\sigma_u}\right)^2 - \left(\frac{\mu_{i^*}}{\sigma_u}\right)^2\right\} - T\ln(\sigma_v) - \ln(\sigma_u) - \ln\Phi\left(\frac{\mu}{\sigma_u}\right)$$

where $\mu_{i^*} = \dfrac{\mu\sigma_v^2 + \sigma_u^2 \sum_t \varepsilon_{it}}{\sigma_v^2 + T\sigma_u^2}$ and $\sigma_* = \dfrac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + T\sigma_u^2}$

The maximum likelihood estimation approach of the log-likelihood function of the model is obtained by summing $\ln L_i$ over i where, $i = 1,...,N.$ Hence, MLE of the unknown parameters is obtained by maximizing the log-likelihood function (Colombi et al., 2011; Filippini and Greene, 2016; Greene, 2008; and Kumbhakar et al., 2013). Following the estimation of the parameters of the model, inefficiency for each i can be computed from either the mean or the mode. In this research, the estimation procedures in Equations (2.17) through (3.19) are adapted from Kumbhakar et al.'s (2015) estimation techniques.

Model 4: Inefficiency effects model

The existence of technical inefficiency in production can be determined through the stochastic production function. Heshmati (2013) and Tsionas et al. (2015) discuss technical inefficiency's effects and the error components models as the two variants of the stochastic frontier where the efficiency effects explain the degree of inefficiency. Battese and Coelli's (1995) inefficiency effects model for the technical inefficiency effect in the SF model using panel data followed the simple stochastic frontier production function as:

(2.22) $Y_{it} = \alpha_0 + f(K_{it}, L_{it}, M_{it}; \beta) + yr_t + v_{it} - u_{it}$

This model focused on the u_{it} non-negative random variables associated with technical inefficiency of the distance function. In this model u_{it} is assumed to be independently distributed and found using a truncation of the normal distribution at zero with mean $Z_{it}\delta$ and variance δ^2, that is, $N(Z_{it}\delta, \delta^2)$. Where Z_{it} is also the $(1xn)$ vector of explanatory variables which relate to technical inefficiency of an airport's output over time, and δ is $(nx1)$ a vector of the unknown coefficient. Model 4 is specified as the original stochastic frontier panel data approach (Colombi et al., 2011; Filippini and Greene, 2016; Kumbhakar et al., 2013; and Tsionas et al., 2015).

One unique aspect of this model is that the technical inefficiency effects are assumed to be a function of a group of explanatory variables that include some inputs from the stochastic frontier model which can provide inefficiency effects. This can be expressed as derived technical inefficiency effects of u_{it} that also assumes a function of another set of explanatory variables specified as vector Z_{it} and an unknown vector of coefficients δ to be estimated. The independent variables in the inefficiency model can include some inputs of the stochastic frontier model which can provide the technical inefficiency effect (Battese and Coelli, 1995).

The technical inefficiency effect u_{it} in the stochastic frontiers is specified as a function of its determinants (described in Heshmati, 2013) and is written as:

(2.23) $u_{it} = Z_{it}\delta + w_{it}$

here the variable w_{it} is random and defined by the truncation of the normal distribution with zero mean and constant variance (δ^2) and the point of truncation is specified as $-Z_{it}\delta$ while the inequality of $w_{it} \geq -Z_{it}\delta$ is also consistent with the assumptions of u_{it}. Finally, this model is estimated by using the MLE method (Baten et al., 2009). Thus, Battese and Coelli (1995) proposed the maximum likelihood method for simultaneously estimating both the parameters of the stochastic production frontier model and the technical inefficiency model in one step.

On the other hand, technical efficiency considering total variations in an output from the frontier level of output (Battese and Coelli, 1995; Baten et al., 2009) is defined by the ratio $\gamma = \dfrac{\delta_u^2}{(\delta_u^2 + \delta_v^2)}$. Accordingly, the variance parameter γ should lie between the interval $[0,1]$. Since this model assumes truncated and half-normal distribution, the ratio of airport specific variability to total variability γ is positive and significant implying that airport-specific technical efficiency becomes important in explaining total variability of the outputs that it produces. Imposing restrictions and generalized likelihood ratio tests help test the hypothesis of the distribution of the random variable of technical inefficiency and the residual error terms. Hence, the generalized likelihood ratio statistic (Baten et al., 2009) is defined as:

$$\lambda = -2\left(\ln\left[L(H_0)\right] - \ln\left[L(H_1)\right]\right)$$

where the values of $\ln\left[L(H_0)\right]$ and $\ln\left[L(H_1)\right]$ indicate the log-likelihood function for the frontier model within the null and alternative hypotheses. For instance, if the null hypothesis is $\gamma = 0$, technical inefficiency's effect will not be present in the model. Similarly, λ will have mixed chi-square distribution considering the degree of freedom and number of imposed restrictions.

The technical efficiency of the production function for 13 airports at time period t is:

$$u_{it} = \delta_0 + \delta_1 Z_1 + \delta_2 yr_t + w_{it}$$

(2.24) $TE_{it} = \exp(-u_{it}) = \exp(-Z_{it}\delta - w_{it})$

$$TE_{it} = \exp(-u_{it}) = \exp(-\delta_0 - \delta_1 Z_1 - \delta_2 yr_t - w_{it})$$

Hence, technical efficiency is predicted based on the conditional expectation in accordance with the assumptions of the model.

Model 5: Marginal effects model

Marginal effects in inefficiency analyses can be estimated using Wang's (2002) model of production frontier taking some feature of KGMHLBC and CFCFGH models. Following equation (2.12) the efficiency terms can be expressed as:

(2.25) $u_{it} \sim N(0, \sigma_u^2)$

(2.26) $u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2)$

(2.27) $\mu_{it} = Z_{it}\delta$

(2.28) $\sigma_{it}^2 = \exp(Z_{it}\gamma)$

where u_{it} is the inefficiency effect, indicating a non-negative truncation of a normal random variable and the variable z_{it} is the constant value associated with inefficiency with δ and γ the corresponding coefficients. Wang's (2002) model is developed as a special case of KGMHLBC and CFCFGH (that is, Kumbhakar, Ghosh, and McGuckin (1991), Huang and Liu (1994), and Battese and Coelli (1995) as KGMHLBC while Caudill and Ford (1993), Caudill, Ford, and Gropper (1995), and Hadri (1999) as CFCFGH). As Wang explains, KGMHLBC focuses on replacing z_{it} using a constant number 1 in Equation (2.28) while for CFCFGH substituting 0 in Equation (2.27), despite Kumbhakar and Wang (2010) stating that the boundary between the two is not explicitly defined.

Kumbhakar and Wang (2010) explain that the marginal effects of the mean and the variance of inefficiency (u_{it}) are:

$$(2.29)\quad \frac{\partial E(u_{it})}{\partial z[k]} = E'(u_{it}) = f'(\mu_{it},\sigma_{it}) = \sigma_{it}[k]\left[\frac{\mu_{it}}{\sigma_{it}} + \frac{\phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}\right]$$

$$(2.30)\quad \frac{\partial V(u_{it})}{\partial z[k]} = V'(u_{it}) = g'(\mu_{it},\sigma_{it}) = \sigma_{it}[k]\left[1 - \frac{\mu_{it}}{\sigma_{it}}\left[\frac{\phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}\right] - \left[\frac{\mu_{it}}{\sigma_{it}} + \frac{\phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma_{it}}\right)}\right]^2\right]$$

Respectively, where ϕ is the probability density and Φ is the cumulative distribution functions of a standard normal variable. Both equations imply that the mean and variance of u_{it} are expressed as functions of μ_{it} and σ_{it}. Both are observation-specific and have an exogenous influence.

Wang (2002) assumes the marginal effect of the z variable on inefficiency to be non-monotonic that depends on the values of the exogenous variables and its impact on inefficiency can change the direction of the inefficiency. On the other hand, KGMHLBC assumes the marginal effect of the inefficiency model as monotonic indicating that exogenous variables' mean and variance of inefficiency can increase or decrease the same way or in the opposite direction. This also implies that the direction of the impact is monotonic and is determined by the sign of the δ coefficient (Wang, 2002).

In our study, airport category is assumed as a constant and related to KGMHLBC in which σ_{it}^2 is constant and $\gamma[k] = 0$ for all k. Thus, the marginal effect is equal to the slope of the coefficient $\sigma[k]$ multiplied by an adjustment function as (2.29) and the sum of adjusted slope coefficients (2.30). Similarly, in the model with a constant σ_{it}^2 the effect of the variable on the conditional statistics is also monotonic. This is a simple model of marginal effects on $E\left(u_{it}/\hat{e}_{it}\right)$ which is similar to (2.29) except μ_{it} and σ_{it} are replaced by μ_* and σ_* as:

(2.31) $$\mu_* = \frac{\sigma_u^2 \mu_{it} - \sigma_{it}^2 (y_{it} - x_{it}\beta)}{\sigma_u^2 + \sigma_{it}^2}$$

(2.32) $$\sigma_* = \frac{\sigma_u \sigma_{it}}{\sqrt{\sigma_u^2 + \sigma_{it}^2}}$$

By using a similar procedure, the variance marginal effect of $V\left(u_{it}/\hat{e}_{it}\right)$ μ_{it} and σ_{it} can be replaced by μ_* and σ_* in Equation (2.30).

5. Estimation and Discussion of the Results

The analysis of production efficiency of Ethiopian airports' used a stochastic frontier panel data approach in studying 13 international and domestic airports covering the period 2002-17. The study focused on variables such as annual number of passengers transported and air freight cargo transported in thousands of kg aggregating production outputs. Man-day productive hours of each employee, total capital investments in the construction of terminal buildings, runways, aprons, and other facilities including power house, power sub-station, and warehouses having big cold rooms and reserve generator installation at constant prices were categorized as capital inputs. Besides, regular maintenance and repairing expenses, and administrative or operation expenses excluding wages and salaries for employee were categorized as a third input variable in the airport production efficiency analysis.

As standard econometric models' specifications and model selection approach, the translog production function was examined and tested for its suitability. However, it was found that the translog function did not converge and there was no meaningful estimation result generated. Thus, the simpler Cobb-Douglas production function was selected and the basic assumptions of the model's specification were fulfilled which enabled us to proceed with the panel data stochastic frontier approach in analyzing Ethiopian airports' production efficiency. Model selection among the fixed-effects and random-effects models was done using the Hausman test. The chi-square result was 62.16, and prob.>chi-square which was strongly significant at the 1 percent level of significance. This is in favor of the fixed-effects model. This shows that the fixed-effects model approach of the time-invariant and time-varying panel data models was a preferable estimation method. In addition to fixed-effects test, Kumbhakar et al.'s (2014) models, maximum likelihood estimation techniques and distance approach of inefficiency effects were also used for increasing the efficiency of the estimates.

The approximate efficiency levels of selected airports were investigated by studying their short-run transient technical efficiency and long-run/persistent technical efficiency. The estimation results of these specified models are given in Table 2.6.

Table 2.6. Production estimation of the time-invariant fixed-effects model (NT=208 observations)

Elasticities	Coef.	Std. Err	p>|t|	95% confidence interval	
Logarithm of man-day productive hours (lnL)	0.27	0.22	0.235	-0.175	0.710
Logarithm of net real capital (lnK)	0.03	0.04	0.560	-0.081	0.149
Logarithm of real maintenance and repairing (lnM)	0.19**	0.09	0.031	0.176	0.358
Yearly trend (Yr)	0.13***	0.03	0.000	0.084	0.179
Constant	-255.00***	47.60	0.000	-348	-161
Rho (R^2)	0.750				
Corr. (u_i, Xb) = 0.4997, F (4,191) = 65.18, Prob > F = 0.0000					
F test that all u_i = 0: F(12, 191) = 15.44, Prob > F = 0.0000					

Note: Author's calculations (2019).

The time-invariant estimation results of the fixed-effects model are presented in Table 2.6. Hence, among the inputs considered, maintenance and repairing expenses was positive and statistically significant. Similarly, annual productivity (yr) was also positive and strongly significant. This shows that a 1 percent change in maintenance and repairing expenses will result in a 0.19 percent change in the value of passenger and freight cargo outputs in the same direction. This change, though positive and significant, is inelastic which means that an increase in the output is accompanied by an amount which is less than the increase in inputs. All the other remaining inputs' parameters (L and K) are positive but insignificant. Since the margin of error of the coefficient of man-day productive hours of the labor force input as well as net capital investment input's values are higher than 10 percent, the output is not responsive to any change in the unit input of labor force and capital investment.

The last coefficient of the time trend yr (0.13) is positive and statistically significant. This explains that productivity of passenger and freight cargo output per man-day productive hours, per net capital investments, and per maintenance and repairing expenses, increased in real values by approximately 13 percent per annum on average across all airports during the study period 2002-17.

In accordance with the time-invariant fixed-effects model the sum of the input coefficients of lnL, lnK, and M showed decreasing returns to scale since the sum of all the coefficients (elasticities) was positive but less than one. A 1 percent change in aggregate inputs of lnL, lnK, and lnM will make a 0.49 percent change in the value of passenger movements and transported freight cargo outputs. The efficiency levels of all the airports are given in Table 2.7.

Table 2.7. Summary statistics of airports' production efficiency using the FE model (208 observations)

Variables	Mean	Std. Dev.	Minimum	Maximum
Efficiency	0.1215	0.2552	0.0087	1.0000

Note: Author's calculations (2019).

Time invariant efficiency in the fixed-effects model is obtained without a distributional assumption and the result is estimated to be about 12.15 percent on average during the period 2002-17. This result is similar to the 15.52 average efficiency level found using Kumbhakar et al.'s (2015) model titled 'Practitioner's Guide to Stochastic Frontier Analysis Using Stata'. This implies that airports' inefficiency levels on average were 87.85 percent during the study period. The basic assumption of this model is that technical inefficiency is individual specific and time-invariant, that is, it may vary across airports but is constant over time. It should be noted that efficiency estimates are sensitive to adding or dropping outlier observations, namely airports with either very high or very low values of α_1.

The next estimation result includes the time-varying technical inefficiency model. In the above time-invariant models, the inefficiency effects may not change over time except that there could be individual level differences. This means that inefficient airports did not improve over time which further means that there was no change in their management during the study period (unless it was very short time). Whereas over a long period of time it is implausible for inefficient airports to stay inefficient for an extended period of time. It is possible that basic public infrastructure like airports, airlines, electricity, and water stay constant with the help of government subsidies. In a competitive market, such assumptions are unrealistic and it is difficult to derive any useful policy recommendations from them. Hence, the time-varying inefficiency effects model is more general as it considers a variety of distributional assumptions. The time varying model is also classified into fixed or random-effects models. To separate its persistent and time-varying transitory inefficiency components, the estimation follows a sequence of estimation steps.

Using the simple and restrictive assumption of the Cobb-Douglas production model, the estimation results are presented in Table 2.8. These include Kumbhakar et al.'s (2014) model's results. Hence, the model is specified in the form of a log of man-day productive hours, log of net capital investments, and log of real maintenance and repairing expenses without salaries and wages that estimated using Kumbhakar et al.'s (2014) procedure. In the first estimation, the parameter's estimates are obtained using a standard fixed-effects panel data regression model.

Table 2.8. Production estimation results based on Kumbhakar et al.'s (2014) model

Elasticities	Coef.	Std. Err.	Z	95% Confidence interval	
Logarithmic form of man day productive hours (lnL)	1.36***	0. 103	13.12	1.15	1.56
Logarithmic form of net real capital (lnK)	-0.107*	0. 055	-1.91	-0.22	0.003
Logarithmic form of real maintenance and repairing (lnM)	0.002	0. 080	0.25	-0.15	0.192
Constant	2.370	1.910	1.24	-1.39	6.132
Rho (R2)	0.540				
F(3,192) = 67.23 corr(u_i, Xb) = 0.1128 Prob > F = 0.0000					
F test that all u_i=0: F(12, 192) = 18.25 Prob > F = 0.0000					

Note: Author's calculations (2019).

The estimation results in Table 2.8 show that the statistical significance of the variable man-day productive hours (L) is strongly significant. This implies that a 1 percent change in man-day productive hours of the workforce input will result in a 1.36 percent change in the value of passenger movements and freight cargo transported. Since the man-day productive hours (L) value (coefficient) is greater than one, the input variable has a highly elastic relation with output and the increase in outputs is greater than the increase in inputs, the returns to scale of this Cobb-Douglas production function keep increasing. Similarly, the overall returns to scale model assumes that all inputs lnL, lnK, and lnM have increasing returns to scale. The value of capital investment is significant with unexpected sign indicating that an increase in capital investment by one percent leads to decrease passenger and freight cargo output by -0.107 percent. This might indicate an idle investment or production of an output is below the capacity of the airports.

Following the estimation of input elasticities, prediction and estimation of inefficiency effects are separated as persistent and transitory inefficiency components based on Kumbhakar et al.'s (2014) estimation technique. Table 2.9 gives the average mean efficiency of all the airports.

Table 2.9. Average mean efficiency of all the airports over the study period based on Kumbhakar et al.'s (2014) model

Model	Components	Mean	Std. Err.	Minimum	Maximum
Model 2	Residual	99.48	0.000	99.47	99.49
	Persistent	56.34	15.30	25.42	80.03
	Overall	56.05	15.22	25.29	79.61

Note: Author's calculations (2019)

The efficiency estimation results based on Kumbhakar et al.'s (2014) model show that Ethiopian airports preformed at a higher short-run or transitory efficiency as indicated by the residual efficiency of 99.48 percent on average across airports as well as across the study period. In terms of long-term persistent efficiency, the average efficiency score is about 56.34 percent. In other words, the persistence inefficiency levels of all the airports on average during the study period was 43.66 percent implying that all the airports will continue to be inefficient in the future. Similarly, the overall efficiency condition is also almost similar to the persistent efficiency level with a score of 56.05 percent or with an overall inefficiency level of 43.95 percent. According to these estimation results, Ethiopian airports produced actual passenger and freight cargo outputs that were 43.95 percent lower than the potential or maximum possible efficiency of passenger and freight cargo outputs. Thus, there exists a potential for improving the airports' performance.

MLE estimation results

The maximum likelihood estimation technique helps to generate higher efficiency. Though the model required a strong assumption of normality, this was also supported by the skewness and LR test statistics reported in Table 2.12 (see also Table 2.13).

Accordingly, MLE estimations of the coefficients (elasticities) and subsequent efficiency estimations are reported in Table 2.10.

Table 2.10. Production estimation results using the MLE method (208 observations)

Elasticities	Coef.	Std. Err.	z	95% Confidence interval	
Logarithm of man-day productive hours (lnL)	1.37***	0.095	14.36	1.190	1.560
Logarithm of net real capital (lnK)	-0.086	0.050	-1.62	-0.190	0.018
Logarithm of real maintenance and repairing (lnM)	0.063	0.080	0.79	-0.094	0.222
Constant	1.290	1.580	0.82	-1.800	4.390
Rho (R^2)	0.540				
LR chi2(3) = 157.87, Log likelihood = -233.979, Prob. > chi2 = 0.0000					
LR test of sigma_u=0: chibar2(01) = 105.38 Prob >= chibar2 = 0.000					

Note: Author’s calculations (2019).

The estimation results of the maximum likelihood approach presented in Table 2.10 have nearly similar results as those in Kumbhakar et al.’s (2014) Model 2 (Table 2.8). Among the three input variables considered in the study man-day productive hours representing an active labor force was positive and statistically significant. This means that every 1 percent increase in man-day productive hours at each airport, resulted in a 1.37 percent increase in the value of aggregated passenger movements and airfreight cargo transportation. This result shows that a change in the output amount was much greater than the change in input amount in terms of effective man-day productive labor hours. Since the change is greater than one, it shows that the parameter is highly elastic in nature while the remaining two inputs are statistically insignificant implying that outputs of passenger movements and cargo freight transportation are not responsive to changes in capital investments and maintenance and repairing and other operating expenses not including salaries and wages. Similarly, the overall returns to scale of the Cobb-Douglas production function exhibit increasing returns to scale since the sum’s input elasticities lnL, lnK, and lnM are greater than one.

To increase the efficiency of the estimation techniques, separation of firm effects into both firms’ latent heterogeneity (Greene, 2005a, 2005b) and persistent/long term inefficiency effects is necessary. Separation into time-varying or transitory/short-run inefficiency effects and random shock effects was done for estimating the model by applying the maximum likelihood estimation method using Kumbhakar et al.’s (2014) separation procedure.

Table 2.11. Mean MLE production efficiency of all airports over the study period

Model	Efficiency components	Mean	Std. Dev.	Minimum	Maximum
Model 3	MLE-Residual	99.58	0.00	99.57	99.58
	MLE-Persistent	50.51	20.47	14.98	81.93
	MLE-Overall	50.30	20.38	14.92	81.59

Note: Author's calculations (2019).

The estimation results of the maximum likelihood approach are reported in Table 2.11. As stipulated, the residual efficiency levels of all airports on average was 99.58 percent while the persistent and overall efficiency was 50.51 percent and 50.30 percent respectively. The mean persistent inefficiency and overall inefficiency levels of all the airports was 49.49 percent and 49.70 percent respectively. This means that on average the actual output of passenger and freight cargo was approximately 49.70 percent lower than the maximum potential/possible output level.

As indicated in Kumbhakar et al. (2017) and Rashidghalam et al. (2016), MLE has higher efficiency compared to other efficiency analyses. Hence, the estimation results show that in both the approaches, almost all airports had higher short-run or time-varying transitory efficiency levels. Whereas in terms of persistent technical efficiency, Kumbhakar et al.'s (2014) model's estimation score is 56.34 percent, the actual level of persistent efficiency is 50.51 percent using MLE. Similarly, the overall technical efficiency is 50.30 percent instead of 56.05 percent (model 2).

The implications of these estimation results from an economic point of view means that airports need to increase the productivity of all their input resources so as to reach the maximum potential output level based on the output oriented or input oriented technical efficiency models. In the latter case, this is interpreted to mean that higher efficiency can be achieved by maintaining the existing actual output levels by reducing excess inputs like facilities such as capital investments, maintenance and repairing, and human capital deployment (if there is any wastage of resources). Since the inefficiency level is very high (49.70 percent), it requires government interventions to bring about necessary structural changes in the industry.

Robustness testing of the production stochastic frontier models

The specification of the model can be tested by using the probability of skewness test for normality of the model. The normality test shows that the p-value for skewness was less than 0.001 for the error term. It was statistically significant implying that the null hypothesis of no skewness was confidently rejected. This finding is in favor of a left skewed error distribution. This result confirms that the model is properly specified. Hence, we can proceed to the next stage of estimating the model specified as a stochastic frontier model.

Table 2.12. Skewness/kurtosis for a normality test

Model	Variable	Probability			Joint
		skewness	kurtosis	Chi2(2)	Prob>chi2
Maximum likelihood	Err.	0.000	0.000	55.43	0.000
estimation (MLE)	Muf.	0.032	0.036	9.02	0.011
Kumbhakar, Lien and	Err.	0.000	0.000	57.86	0.000
Hardaker (KLH)	Muf.	0.219	0.598	1.79	0.410

Note: Author's calculations (2019).

Table 2.13. Critical values of the mixed chi-square distribution

Model	Test statistics	Significant level (critical value)			
Kumbhakar et al. (2014)	2.129	DF	0.100	0.050	0.010
Maximum likelihood (MLE)	8.093	1	1.642	2.705	5.412

Note: Author's calculations (2019).

Table 2.13 shows the log-likelihood ratio (LR) test's results for technical inefficiency. The degree of freedom for the restricted test is only one parameter (that is, σ_u^2). The LR calculated test statistics of the MLE model is 8.093. The critical value of the test statistic at 1 percent and 10 percent significance levels is 5.412 and 1.642 respectively. When compared to the calculated test with the critical values, the null hypothesis of no technical inefficiency is rejected at the 1 percent level. Likewise, the test statistics for Kumbhakar et al.'s (2014) model are 2.112. This result indicates a rejection of the null hypothesis of no technical inefficiency at less than the 10 percent level and it confirms the existence of technical inefficiency in the model. In both the cases, the stochastic frontier model assures the presence of technical inefficiency and from there it is possible to proceed and analyze airports' technical inefficiency using the stochastic frontier model.

It is a fact that there exist high variations in technical efficiency of the models over time. Hence, the use of average values for further interpretations may be misleading and a comparison of efficiency scores across airports is more preferable.

Table 2.14. Mean production efficiency comparison of airports (2002-17, in %) (208 observations)

ID	Airports	Model 1 FE (%)	Model 2 KLH (%)			Model 3 MLE (%)		
		LR-PE	LR-PE	SR-RE	OTE	LR-PE	SR-RE	OTE
1	AABIA	100.0	80.00	99.50	79.61	81.93	99.58	81.59
2	Dare Dawa	8.33	46.08	99.48	45.84	32.22	99.58	32.09
3	Mekelle	7.62	58.88	99.48	58.57	48.82	99.58	48.62
4	B/Dar	6.76	52.25	99.48	51.98	39.92	99.58	39.75
5	Jimma	1.80	29.24	99.48	29.08	17.36	99.58	17.36
6	Gonder	6.07	53.56	99.48	53.28	43.10	99.58	43.28
7	Axum	6.26	60.54	99.48	60.23	54.94	99.58	54.71
8	Lalibella	5.74	65.41	99.48	65.07	63.93	99.58	63.66
9	Gambella	4.76	71.03	99.48	70.66	73.65	99.58	73.34
10	Arbaminch	0.87	25.42	99.48	25.29	14.98	99.58	14.92
11	Gode	3.51	67.32	99.48	66.97	68.57	99.58	68.29
12	Assosa	1.98	52.53	99.48	52.26	44.49	99.58	44.31
13	Jijiga	4.26	70.15	99.48	69.79	72.41	99.58	72.11
	Average	12.15	56.34	99.48	56.05	50.51	99.58	50.30

Note: Author’s calculations (2019).

Table 2.14 gives a comparison of the mean efficiency of the airports based on the three models’ estimation results across airports. This relative comparison of the efficiency results also shows the existence of significant variations between time-invariant (distribution imposing assumption) of fixed-effects and the time-varying (distribution free assumption) of Kumbhakar et al. (2014) and MLE approaches. Besides, the average mean efficiency scores vary significantly between persistent and transient efficiency components. In the short run as indicated by residual efficiency component the estimation results in both Model 2 KLH and Model 3 MLE is nearly 100 percent implying that airports are temporarily efficient.

Since their distributional assumptions vary with and without time, the efficiency results also vary. The mean efficiency for the fixed-effects model during the study period was approximately 12.15 percent. It is assumed that an efficient airport is expected to score 100 percent and 12.15 percent efficiency implies that most of the airports studied were on average up to 87.85 percent inefficient. What is shocking is that almost all Ethiopian airports had very low levels of efficiency. Though these extreme levels need a further analysis, taking Addis Ababa as the benchmark, all the remaining airports’ efficiency levels were below 10 percent during 16 years of the study period and this will persist in the future despite the limitation of constant inefficiency assumption of the fixed-effects model.

In Kumbhakar et al.'s (2014) model the highest persistent efficiency was scored in Addis Ababa International Airport (80 percent), followed by Gambella (71.03 percent), Jijiga (70.15 percent), and Gode (67.32 percent) airports. On the other hand, the three least performing airports with the lowest persistent efficiency levels were Dire Dawa (46.08 percent), Jimma (29.24 percent), and Arbaminch (25.42 percent). Persistent efficiency values for the rest of the five airports was between 50 percent and 60 percent. In terms of overall technical efficiency, Addis Ababa (79.61), Gambella (70.66), Jijiga (69.79), and Gode (66.97) were the most efficient airports.

The estimation results of the MLE model show that some differences existed in efficiency across airports and in inefficiency levels. For instance, the most efficiently performing airport using the MLE model was Addis Ababa International Airport (81.93 percent), followed by Gambella (73.65 percent), Jijiga (72.41 percent), and Gode (68.57 percent). On the other hand,

Considering the estimation results of the three models discussed earlier, the model with the highest efficiency was MLE. Therefore, the relevant estimation results of this study which help draw the final conclusions in the relative analysis are those which give the overall technical efficiency levels of airports using the MLE approach. Hence, as compared to other airports, the most efficient airports were those that had the best as well as least scores in Kumbhakar et al.'s (2014) and MLE model. That is, Addis Ababa (81.59 percent), Gambella (73.34 percent), Jijiga (72.11 percent), and Gode (68.29 percent) which had the best overall efficiency in MLE approach. In contrast, some least performing airports in overall efficiency levels were Dire Dawa (32.09 percent), Jimma (17.36 percent), and Arbaminch (14.92 percent). Following the efficiency analysis based on the MLE model in Table 2.12, on average, the overall efficiency of all the 13 domestic and international airports according to this study was about 50.30 percent. The findings of the MLE model's efficiency results are preferred relative to KLH-2014 and fixed-effects models.

Airports with low levels of efficiency performed poorly as compared to maximum possible or potential outputs in passenger movements and transporting airfreight cargo. According to an efficiency theory analysis, transitory inefficiency can change over time while persistent inefficiency cannot change over time or across individual firms unless there are structural policy changes. As persistent inefficiency is very high, the government's policy interventions are very crucial for bringing about structural changes and tackling future inefficiencies of Ethiopia's airports.

Table 2.15. Production estimation results using Battese and Coelli's (1995) distance and Wang's (2002) marginal inefficiency effects models'

Distance frontier Production function:	BC-95 Distance effects Model 4			Wang (2002) marginal effect Model 5		
	Coeff.	Std. Err.	Z	Coeff.	Std. Err.	Z
lnL	-0.052	0.151	-0.35	1.136***	0.119	9.48
lnK	0.081	0.056	1.45	-0.108*	0.055	-1.98
lnM	0.44***	0.101	4.35	-0.289***	0.089	-3.25
Yr	0.18***	0.020	9.01	-	-	-
Constant	-355.428***	40.62	-8.75	12.99***	1.96	6.62
Inefficiency function (mu)						
Z	-0.802***	0.120	-6.59	-0.945***	0.117	-8.05
Constant	7.1489***	0.808	8.85	9.23	0.964	9.59
Sigma_u	0.8307***	0.039	14.89	-	-	-
Sigma_v	0.1059	0.082	1.29	-	-	-
Lambda	7.8442***	0.108	72.49	-	-	-
Sigma_u(Z)	-	-	-	-1.513	0.348	-4.35
Average marginal effect on inefficiency E(U)				-0.968		
Average marginal effect on inefficiency V(U)				-1.820		

Note: Author's calculations (2019).

This chapter followed the panel data approach for estimating the distance function stochastic frontier model including the marginal effect. The estimation results in Table 2.15 first part show that the coefficient of maintenance and repairing expenses was significant and positive as expected, suggesting increases in the same direction with output in the BC-95 model of distance efficiency. Other variables such as the man-day productive workforce and net capital investments in this model were not statistically significant. Passenger and freight cargo outputs were not responsive even at the 10 percent margin of error to an increase or decrease of man-day productive hours of the labor force as well as net capital investments. This may signify underutilization or excessive use of capital and labor resources. In the case of Wang's (2002) model the marginal efficiency effect of man-day productive hours or the labor force parameter (1.136), was positive and statistically significant. Though other such capital investments (-0.108) and maintenance and repairing costs (-0.289) were also significant with an opposite sign. The implications of these results are that for every 1 percentage increase in labor force/man-day productive hours, capital investments and maintenance and repairing associated production increased by 1.136 percent, reduced by 0.108 percent, and reduced 0.289 percent respectively.

The implications of the BC-95 model are that a 1 percent change in real maintenance and repairing expenses will induce a 0.44 percent change in the passenger and freight cargo outputs. Since the estimated coefficient is less than one, the input is low or inelastic in nature. Analogously, the overall estimated sum of all the parameter's coefficients is also less than one. This implies that the distance frontier using the Battese and Coelli (1995) efficiency effect model has an input inelastic nature. According to this model's estimation, the Ethiopian airports that were studied under output levels that were inelastic to input changes.

The coefficient of the time trend (yr) is 0.18 which means that the rate of technical change for the distance inefficiency model is positive and significant suggesting that the dominant effect of output productivity is technical progress over other exogenous factors having an upward looking sign in output function over time. The estimated coefficient implies that every airport's output productivity increased in real terms by about 18 percent per annum on average across all airports over the period 2002-17.

The estimation results for an airport categories (Z) were significant and had the expected negative sign. This shows that technical inefficiency levels will reduce significantly on average by 0.80 percent every year across all the airports under consideration.

The variance model relationship is given by:

$\hat{\sigma}_s^2 = \sigma_u^2 + \sigma_v^2$ and $\hat{\gamma} = \sigma_u^2 / \sigma_s^2$

The square of sigma-u (0.8307) is 0.69 and the square of sigma-v (0.1059) is 0.0112. The total of the square of the variance $\hat{\sigma}_s^2$ =0.7012. Following this functional relationship, the gamma variance parameter is $\hat{\gamma}$=0.98. The gamma variance parameter (0.98) is close to one and its value should normally lie between [0, 1]. Here the ratio of airport specific variability to total variability is positive and significant showing that airport specific technical efficiency is very important for explaining the total variability of passenger and cargo outputs produced/served.

Table 2.16. Test of the hypothesis for the parameters of airport inefficiency frontier models (NT= 208 observations)

Null hypothesis	DF	Log likelihood	X2 values	p-value	Test statistics
$H_0 : \gamma = \delta_0 = \delta_1 = ... = \delta_3 = 0$	2	248.54		0.000	216.93
$H_0 : \gamma = 0$	1		5.412	0.000	31.40
$H_0 : \delta_1 = \delta_2 = \delta_3 = 0$	4	247.49		0.000	206.45

According to Battese and Coelli's (1995) model if the inefficiency effects are stochastic, some input variables are included in the explanatory variables of the inefficiency model. Hence, the test of the hypothesis for the presence of stochastic frontier as well as inefficiency effects is examined using the likelihood ratio test. The test states that inefficiency effects are absent or alternatively inefficiency effects are distributed within the stochastic model and the results are presented in Table 2.16.

In the first hypothesis, it was assumed that if all the components of the Z-vector are equal to zero, technical inefficiency cannot be related to the Z-variables. Since the p-value is significant at 1 percent level, the null hypothesis that states inefficiency effects are absent from the model is strongly rejected. In other words, the assumption is that all components of the Z-vector are equal to zero, technical inefficiency cannot be related to the Z-variables is rejected. Moreover, the second hypothesis is tested with the log likelihood ratio test by computing the restricted and unrestricted models. The unrestricted model is the original one with a log likelihood value of -247.4895 while the restricted log likelihood value is -263.1920.

Thus, LR= $\hat{\lambda}$ =-2[-263.1920-(-247.4895)] =-2(-15.7025) =31.40

The calculated LR test statistics are 31.40 which are higher than the critical value of 5.412 at the 1 percent level of significance. Hence, the null hypothesis which stipulates that inefficiency effects are not stochastic is strongly rejected and this model confirms that the inefficiency effects of Ethiopian airports are stochastic.

The final hypothesis stated that inefficiency effects are not a linear function. At a 1 percent level of significance, the null hypothesis of a non-linear relationship is strongly rejected and the joint effect of the two explanatory variables of the inefficiency of airport outputs are statistically significant. It can be generalized that the inefficiency effect is stochastic and it is related to airport standard categories and the year of observations. In most cases, categories are determined based on services for passengers and aircraft movements. The highly congested airports have more facilities of higher standards while less congested airports have lesser facilities and their standards may also low. Efficiency level of airports as per distance efficiency effect are shown Table 2.18 and FE estimation results are also presented for comparison.

Table 2.17. Mean efficiency score of Battese and Coelli (1995) and FE efficiency model of airports in % (208 observations)

ID	Airports	FE efficiency	Battese and Coelli (1995) Efficiency model
1	Addis Ababa Bole International Airport	100.00	73.92
2	Dire Dewa International Airport	8.33	12.04
3	Mekelle International Airport	7.62	7.89
4	B/Dar International Airport	6.76	7.91
5	Jimma Domestic Airport	1.80	2.90
6	Gonder Domestic Airport	6.07	7.41
7	Axum Domestic Airport	6.26	7.55
8	Lalibella Domestic Airport	5.74	7.34
9	Gambella Domestic Airport	4.76	1.53
10	Arbaminch Domestic Airport	0.87	1.30
11	Gode Domestic Airport	3.51	5.08
12	Assosa Domestic Airport	1.98	2.57
13	Jijiga Domestic Airport	4.26	4.54
Average Airports		12.15	11.98

Note: Author's calculations (2019).

Next we examine the efficiency level as aggregate average efficiency of all airports and of each airport during the study period. The findings of the distance stochastic panel frontier efficiency estimates show that the efficiency levels of all Ethiopian airports were extremely low and below 10 percent though the average efficiency effect was 12 percent. Relatively the best efficiency score was at Addis Ababa International Airport, the busiest airport in Africa, which had a better efficiency at 73.92 percent while Dire Dawa with a 12.04 percent efficiency level stood second in rank. This result is almost similar to the one obtained by using the fixed-effects model. Further, in both the cases the level of efficiency was extremely low despite differences in the assumptions underlying the models.

Marginal effects on production inefficiency

In the production efficiency analysis, airport category specified by ICAO was considered as an exogenous factor for examining efficiency trends in selected Ethiopian airports. The study assumed airport categories as constant and monotonic like KGMHLBC but the estimation procedure followed Wang (2002) and that specified in Kumbhakar and Wang (2010). In this estimation, the coefficient mu is -0.0451 which means that the statistical p-value at 0.000 is strongly significant. Similarly, the coefficient of usigma is -1.513 with a p-value 0.000 which is strongly significant. Accordingly, for these statistical results the variable airport categories is properly specified as it is supported by the obtained data.

The next step is estimating the marginal effects of the inefficiency of the production frontier using the airport category fitted variables. The estimation results of the unconditional expectation of the mean inefficiency value of the average marginal effect E(u) is -0.9681 while the variance inefficiency of average marginal effect on unconditional V(u) is -1.82 where both are negative. Since an increase in airport capacity means an improvement in airport category as per ICAO standards. Thus, an increase in airport capacity in the course of production implies that in the future other things being constant, this will reduce mean technical inefficiency and technical inefficiency uncertainty significantly. In other words, a 1 percentage change in the airport category will result in increased average mean of technical inefficiency by 96.81 percent and variance uncertainty of technical inefficiency by 182.02 percent on average, other things remaining constant.

6. Summary, Conclusion, and Recommendations

Production efficiency is defined as the maximum output that can be attained with the available inputs and technology. The level of measured efficiency can be obtained by the ratio of actual output to maximum attainable output. This study focused on a production efficiency analysis for understanding the efficiency levels of Ethiopian airports.

It investigated the efficiency of 13 domestic and international Ethiopian airports. The production model was specified assuming a Cobb-Douglas stochastic frontier production function covering the period 2002-17. Annual weighted passengers served and freight cargo transported by each airport was the dependent variable. The independent variables were man-day productive hours (all workforces, the real value of maintenance and repairing expenses including other operating expenses except salaries and wages, and long term real capital investments. The estimated inputs (man-day productive hours and maintenance and repairing expenses) and technological changes except capital investments, had overall as expected indicating positive input elasticities indicating a higher productivity growth over time and particularly labour has increasing returns. The value of capital investment is significant with unexpected sign indicating existence of an idle investment or production of an output is below the capacity of the airports.

Time-invariant and time-varying inefficiency approaches of stochastic production and distance frontier models were applied for identifying the inefficiency effects in the fixed-effects and Battese and Coelli's (1995) distance stochastic frontier inefficiency effects model. Besides, a detailed separation of the production efficiency analysis was examined based on Kumbhakar et al.'s (2014) and MLE model. Recently some improvements have been made to the estimation of the efficiency part of the model. The models applied in this study were a result of continuous improvements in many other related models developed previously. In a comparative study, the performance of 12 stochastic frontier panel data models based on the same data is presented in Rashidghalam et al. (2016).

Due to assumption difference, the mean efficiency of KLH 2014 and MLE varied significantly between persistent and transient efficiency levels. Estimation of the efficiency analysis based on Kumbhakar et al.'s (2014) model following a multi-step method and on average, showed persistent efficiency were 56.34 percent while the residual efficiency was 99.0 percent. Finally, KLH 2014 overall efficiency of all 13 domestic and international airports was about 56.05 percent. On the other hand, the maximum likelihood estimation (MLE) was also estimated following Kumbhakar et al.'s (2014) separation procedures. Accordingly, persistent efficiency and overall efficiency reduced to 50.51 percent and 50.30 percent respectively while the residual efficiency remained the same as in Kumbhakar et al.'s (2014) model.

The mean efficiency of the fixed-effects model during the study period was estimated to be about 12.15 percent. It is assumed that an efficient airport is expected to score 100 percent and a 12.15 percent efficiency implies that most of the airports studied were highly inefficient. Efficiency effects based on the distance stochastic panel frontier were estimated and found to be extremely low (12 percent). The busiest airport Addis Ababa had a relatively better efficiency score (73.92 percent) while the others except Dire Dawa were below the 10 percent level. What is shocking is that almost all Ethiopian airports had very low levels of efficiency. Though these extreme low levels of efficiency need a further analysis, taking Addis Ababa as the benchmark the remaining airports' efficiency levels were below 10 percent during the study period and this will very likely persist in the future. Since the time-invariant part of persistent or long-run efficiency is very low, the problem of inefficiency will stay for a long period of time unless there are urgent government interventions for bringing in necessary structural policy changes. The negative and highly significant sign of the coefficient of airport categories (Z) shows that technical inefficiency levels will reduce significantly on average by 0.208 percent every year across the airports under consideration.

The estimated efficiency of Kumbhakar et al.'s (2014) model was relatively higher compared to Battese and Coelli's (1995) distance function and fixed-effects approaches. Besides, MLE is also assumed to be more effieint. In MLE model the highest persistent efficiency was at Addis Ababa International Airport (81.93 percent), followed by Gambella (73.65 percent), and Jijiga (72.41 percent) airports. On the other hand, the least persistent efficiency levels were at Dire Dawa (32.22 percent), Jimma (17.36 percent), and Arbaminch (14.98 percent) airports. The values for most of the other airports were between 40 percent and 70 percent. Overall average mean MLE approach production efficicny was 50.30 percent for all airports during the study period.

Taking the four models' estimations, the technical inefficiency levels at all the airports were high showing the underutilization of airport infrastructure. Besides, since persistent or long-run efficiency is very low, the problem of inefficiency will stay for a long period of time unless urgent measures are taken and implemented by the government. Hence, government's policy interventions required to bring about structural changes to tackle future inefficiencies of Ethiopia's airports. Accordingly, this research calls for the need for developing competitive long-term and short-term strategies that can attract more air traffic customers and expand revenue generating capacities to compensate for airports' capital infrastructure, labor input, and other resources' mobilization and utilization. Classic customer handling and policy and incentive schemes should be introduced for increasing passenger demand, supporting infant private airline operators, and encouraging low cost carriers for effectively using the infrastructure at airports which lies idle for hours every day.

Airports/airlines passengers and cargo volume should be increased by introducing price incentive for the airlines. Particular attention should be paid to increasing demand for domestic air transport. The negative and highly significant sign of the technical inefficiency of an airport's facilities means an increase in basic airport facilities will reduce its technical inefficiency. This requires the airport administration to focus on providing basic airport facilities in parallel with the growth in air traffic passengers. This might include an airport master plan and design development. Attention also needs to be paid to issues of corporate social responsibility and environmental sustainability of the aviation industry. Implementation of a circular economy's principles of reducing, reusing, and recycling of material will support airports' green oriented policies thus helping achieve the UN initiated sustainable development goals.

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Chapter Four – Paper 3

Labor Use Efficiency of Ethiopian Airports

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Abstract

Labor use efficiency optimizes the minimum labor requirements and enables a reduction in the cost of production for a given output. This study analyses labor use efficiency of Ethiopian airports using an input requirement function approach. The study considers panel data for 13 international and domestic airports covering the period 2002-17. The variables used are productive labor hours as the dependent variable; workload unit of passenger and freight cargo transported as outputs; and average wage, capital intensity per labor hour; and energy consumption per unit of output as the independent variables. In this study the fixed-effects, KH-1995 model of separating persistent and transitory inefficiency (the alternative multi-step model), and maximum likelihood estimation (MLE) techniques are used. Among the determinants' variables only average wage was statistically insignificant. The study concluded that labor use and airport output were complementary hence expansion of airport facilities is recommended. Capital, energy, and maintenance and repair inputs substitute labor use. The study also estimates the technical efficiency levels of airports and decomposed into persistent and residual components. MLE and alternative multi-step models show that time-invariant persistent efficiency was on average 49.65 percent and 50.67 percent while the overall efficiency was 49.60 percent and 50.59 percent respectively. Despite these minor differences, many domestic airports performed relatively higher compared to international airports. Thus, deployment of resources above the minimum requirements should be reconsidered as a source of cost reduction. Besides, airports having higher persistent inefficiency will continue to remain inefficient which may necessitate structural changes and revision of employment and labor use policies so as to increase their labor productivity in addition to long run and overall economic growth.

Keywords: labor use; productivity; persistent and transient efficiency; airports; Ethiopia

JEL Classification Codes: C12; C13; C14; C23; D24; C33; C5; J23;

1. Introduction

The Ethiopian economy has been growing rapidly since 2000. The main contributing factors in this are strong government interventions and policy direction towards mobilization of public resources for investments in economic infrastructure and human capital development (Shiferaw, 2017). In any country, the most important productive resources are its workforce and the level of human capital it has. Countries have different levels of workforces as well as their rankings on the Human Development Index (HDI) depending on their economic development. According to Shiferaw (2017) Ethiopia is far behind many other low-income countries in terms of its HDI ranking. Using the 2014 Human Development Report he shows that in Ethiopia the adult population years of schooling was 50 percent lower than the average for sub-Saharan Africa (SSA). Human capital resources are key actors that can play a significant role in agriculture, the manufacturing industry, and the service sectors including in the air transport sector.

Apart from transporting passengers and freight, the air transport sector in general and airports in particular play a significant economic role as well. The sector contributes to the creation of employment, income generating capacity, and supporting the economy and its globalization. The growth and economic contribution of the aviation industry was illustrated by the Air Transport Action Group-ATAG (2018) when it highlighted that the aviation industry contributed more than 65.5 million jobs worldwide and above US$ 2.7 trillion in revenue to the world economy in 2017. This can positively impact global GDP in the form of direct, indirect, induced, and tourism effects (ATAG, 2018). As the economy of once country grow, the service sector including air transport demand increase and income generating capacity of the aviation industry also increase. Contribution and effect of the aviation industry also depends on the countries' level of economic and human resource development.

The main sources of revenue for the aviation sector are the service charges for transporting passengers and freight cargo. Passenger growth trends can be illustrated taking some of the world's busiest airports as a reference. Airport Council International (2018) shows that the world's busiest airport was Hartsfield–Jackson Atlanta International Airport that handles about 103.9 million passengers per year. The second busiest international airport was Beijing Capital International Airport which serviced

95.8 million passengers in 2017. As per ACI (2018) Dubai International Airport served more than 88.2 million passengers and was ranked the third busiest airport in the world.

In contrast to the advanced world, aviation industries in African countries are relatively small. As a relative comparison, some of the busiest airports in Africa by number of passengers are the South African O. R. Tambo International Airport-Johannesburg (21.2 million) passengers, Cairo International Airport with 15.9 million passengers, and the South African Cape Town International Airport with 10.7 million passengers. Addis Ababa Bole International Airport – Ethiopia served 10.6 million passengers was the fourth busiest airport in Africa in 2017 (ACI, 2018). In general, airlines carried about 4.1 billion passengers worldwide and approximately 3.6 percent of the global GDP measured in value was supported by the aviation industry that was mainly generated in the form of service charges (ATAG, 2018).

The multidimensional contributions of the aviation sector in general and of the airport industry in particular are making global scholars and practitioners pay attention to improving its quality and its provision of sustainable services. This is why contemporary world experience says that there is a need to benchmark the airports and their efficiency measurement is increasing. There are two basic determinant factors of efficiency in airports' development: environmental factors and internal matters that are directly related to the strategic decisions taken by an airport's management. Usually the first one is beyond the management's control and the management has very limited influence over it. The latter is a basic issue and concern of the airports since it is totally under the control of their systems and management. The main concern of all research work is on ways of minimizing the management's inefficiencies (Graham, 2005). It is at this time and for this specific problem that scholars have proposed various alternative solutions.

Decision-makers are seeking information about their airports' performance in relation to other similar airports for measuring their efficiency. Graham (2005) explains that there is no consensus among airports as to what the best management tools are and acquiring similar information about airports is challenging for measuring efficiency because a comparison or benchmarking study requires the same values for each airport. In the recent period, airports have been focusing on more business and following commercially oriented approaches. Similarly, many airports in the advanced world have been privatized as they have been motivated by the need for better and more efficient management. These issues have focused attention on how efficiency matters and airport benchmarking as the most important tools for airports' management in the decision-making process (Graham, 2005).

According to Ulku (2009) during the last three decades, the focus of many airports has been following business and commercially oriented approaches while others have been closely working with scholars on research and development to get benchmarking reports for evaluating their relative efficiency and seeing how they can improve the way they manage the airports. The ultimate focus area of efficiency is generating more revenue for sustainable and efficient business development at the airports. Having various strategies and goals might increase the reliability of benchmarking the best airports.

According to Ulku (2009), the increasing level of competitiveness basically assists airports to survive, gain more market share and market power, generating sustainable demand, and following better strategies in the future. Moreover, airports have various strategies in relation to their level of development. Hence, there is an increasing trend of coping with and using existing resources effectively as frontline solutions. In this regard, Kazda and Hromádka (2011) suggest that the trend of effective utilization of existing resources includes an effective deployment of the workforces, facilities, equipment and all ground handling services on the ramp such as runways, taxiways, and apron area air traffic flow management slots. Similarly, terminal building resources such as stands, gates, and check-in counters should be designed for shortest passenger queues. The frequently observed challenges in many airports are optimization problems that arise at the operational planning and at the integration of system control levels that repeatedly complicate flight schedule changes like delays, re-routings, or aircraft change (Kazda and Hromádka, 2011).

The main drawback for promoting airports' efficiency are the challenges of limited hours of operations, interruptions in system integration, and workforce coordination that have been creating congestion at the Addis Ababa Bole International Airport hub. Consequently, the delays have an impact on other domestic airports. This leads to inconvenience for customer airlines and passengers which could have serious implications when airlines want to have smooth connections from their hub. When such problems occur repeatedly they impact the airport's market share and market power. For addressing these problems, there is a need for using more manpower and resources for supporting airport operations. Hence, additional resources should be fully productive which can help increase the operational, technical, and allocative efficiency of airports through a reduction in idle hours in the facilities and services daily. Hence, optimization of existing resources for coping with the increasing demand and competition to avail additional supplies in the form of additional operational working hours by improving productivity of existing facilities, equipment, and manpower on the one hand and expanding airports' capacity and adding facilities to the systems based on cost-benefit feasibility studies is another possible resource use.

It is a fact that the aviation industry is a networking transport system throughout the world. Thus, Ethiopia is also a part of this global transport system. Despite positive and negative global influences, Ethiopian airport services continue to face inconsistency in delivering quality service, low equipment productivity, and capacity constraints in addressing the fast-growing Ethiopian airlines that require additional equipment and manpower productivity. The current practice of the use of airport facilities is limited to morning and evening flight operations. This implies capital productivity per hour in such terminal buildings, all other required facilities and equipment, and apron, taxiway, and runway working hours per day are low compared to operational versus idle hours. Besides, there is the problem of system integration, skills, experience and coordination of the workforce during operations. Skytrax cutomer review report (2019) showed that Addis Ababa Bole international airport service delivery is far below the required level of customer satisfaction (passengers and airlines).

In empirical literature, labor productivity has been paid extensive attention, though labor use efficiency is not well addressed and it is fair to say it is neglected (Hjalmarsson and Veiderpass, 1992). The need and importance of measuring labor use efficiency is unquestionable. Hence, the objective of this research to examine the labor use role and other determinants factor of labour use during output production, measuring an overall efficiency condition, separating time invariant and time varying labor use efficiency of Ethiopian airports. In addition to benchmarking, this will also help Ethiopian airports to compare and contrast their labor use efficiency. Moreover, this study will also help to drive important policy measures that follow from its findings and recommendations.

More importantly, previous empirical research focuses on labor use efficiency was extremely limited so this research makes a significant contribution to labor use efficiency literature and is unique for the airport sector in particular. This study estimates three models: one, the fixed-effects time-invariant model suggested by Schmidt and Sickles (1984), second, the Kumbhakar and Heshmati (1995) model, and the third MLE time-variant model. The three models cover a whole range of aspects of efficiency and its estimation and a sensitivity analysis of the results.

The rest of this chapter is organized as follows. Section 2 reviews literature, and the data and methodology are described in Section 3. Section 4 gives the methodological framework of the study that includes empirical and theoretical literature on the stochastic frontier models. The model's specifications of the panel data input requirement function are given in Section 5. The model's estimation and a discussion of the results are given in Section 6. Section 7 gives the conclusion and makes some recommendations based on the findings of the study.

2. Literature review

This literature review focuses on productivity related empirical application of labor use and labor productivity. Among the many literature and studies those on labor use efficiency in the service sector and manufacturing industry have been reviewed throughout the world.

The concept of technical efficiency was derived from the technical change concept which was first developed by Solow (1957) and called the residual of production activities. Oh et al. (2012) state that Solow (1957) also made three assumptions when measuring technical change: constant returns to scale, Hicks-neutral technical change, and perfect competition. In addition, the modeling production function has an important role in analyzing returns to scale, technical changes, and growth in rate of total factor productivity. Shiferaw (2017) defines productive capacity in a broad context when he says that it is an integrated outcome of existing and potential natural resources, accumulation of human capital, and a proper setup of institutions contributing to holistic and sustainable economic growth. Productivity also requires nurturing entrepreneurs' skills and fostering innovations.

In labor use efficiency literature, pioneering work has been done by Kumbhakar and Hjalmarsson (1995) for the Swedish social insurance office which considers the frontier production function based on a panel data model using a multi-stage approach. These authors estimated the parameters of a flexible input requirement and decompose technical inefficiency into time invariant and time-varying and residual components. Accordingly, their empirical results show the existence of substantial variations in labor use efficiency among the social insurance offices, though mean efficiency declined over time and there was the presence of economies of scale, thereby implying that most of the offices were found suboptimal in size for labor use.

Battese et al. (2000), studied the deregulation impact and crisis related consequences on productivity and productivity growth in the Swedish banking industry using the translog stochastic frontier panel data model. They also define the labor use frontier in the same way as the frontier model's development originally proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) to account for the random and the previously well-known non-negative technical inefficiency effects. The labor use requirement of the given input and output function in a stochastic frontier application focuses on the production functions where the inefficiency effect is reduced in observed output less than the stochastic frontier output. Battese et al. (2000) investigated the existence of significant technical inefficiency effects of labor use in the Swedish banking industry. They found that technical inefficiency of labor use in Swedish banks was significant. These authors also found that different types of banks, number of branches, total inventories, and year of observation significantly affected the banks' labor use inefficiency. Despite these variations, the overall inefficiency effect was about 12 percent and banks on average used 12 percent more labor compared to the potential fully efficient labor with the given level of output and quasi-fixed inputs.

Labor use efficiency has also been studied in Tunisian manufacturing industries (Haouas et al., 2003). These authors addressed the model of dynamic employment demand with the flexible adjustment parameter and measured labor use employment efficiency among six Tunisian manufacturing sectors over 25 years. The adjustment process was at the industry level and time specific. These authors found that long-run employment demands were highly responsive to output changes. Capital stocks and wages were at second and third place respectively. Besides, large variations were observed in the speed of adjustment for employment as well as degree of labor use among industries. Their study showed that the labor use in the manufacturing industries were the least efficient during the first decade of Tunisian independence (1972-85). Hence, overprotection and subsidies might have contributed to higher mean inefficiency while industries efficiency rates improved during 1986-96 following to liberations. This implies that during the liberalization period labor markets were more flexible and employers could adjust faster than they could in the regulated system.

Bhandari and Heshmati (2005) and Haouas et al. (2003) estimated dynamic labor demand using a flexible adjustment approach. Labor use and its adjustment in Indian manufacturing showed that India's manufacturing sector had considerable dynamism in adjusting its workforce (Bhandari and Heshmati, 2005). Their findings showed that in India long-run labor demands were most responsive to output, followed by capital and wages respectively. They also observed that Indian manufacturing was not inefficient in labor use since the speed of adjustment to employment size was closer to the optimal level.

Swedish saving banks' labor demand and efficiency was analyzed by Heshmati (2001). He applied the flexible translog functional form where demand for labor was a function of wages, outputs, quasi-inputs, and a time variable using the panel data model. In terms of labor demand, output elasticity was positive and wage elasticity was negative implying that labor demand was responsive to changes in both outputs and wages. Following a multi-step procedure an estimation of productivity and efficiency of Swedish saving banks, average labor use efficiency was about 96 percent. This showed that the sample banks were technically efficient in labor use.

Loizides and Tsionas (2002) explain total factor productivity (TFP) measurement and a growing econometric interest in it during the past four/five decades. In particular, TFP has been used for making comparisons across countries and across time. Their model was developed using general indices of technical change and applied to firms assuming that the panel data is homogeneous, and the introduction of fixed-effects can capture the difference.

It is reasonable to assume a model's specifications in the transport sector as producing two types of outputs (Loizides and Tsionas, 2002): passenger and freight transportation.

In most cases, the capital factor input is fixed while maintenance and repairing is considered a variable input. Other factors of production are labor, energy, price of labor, and price of energy. In contemporary globalization, airport infrastructure is categorized as major infrastructure as compared to other infrastructure. Besides, efficiency is a major issue in airports' management, though predominantly the public ownership nature of the airports makes them susceptible to and prone to inefficiency behavior (Barros, 2008). Oh et al. (2012) made a detailed exploration of the dramatic changes, time trend, and general index models for estimating TFP growth, technical changes, and returns to scale for Swedish manufacturing and service industries. They also addressed firm-specific and time-varying technical changes and compared the parametric TFP measure with the non-parametric Solow residual based productivity growth.

The concept of technical inefficiency has remained the same since its inception. According to Farrell (1957) technical inefficiency is the failure to produce the maximum possible output having some given inputs. Couto and Graham (2009) add that allocative inefficiency occurs as a result of wrong or sub-optimal choice of input proportions given their prices. Existence of both inefficiency types increases the total cost of production or cost of rendering services. Labor productivity, on the other hand, has been defined by Heshmati and Rashidghalam (2018) as a firm's ability to generate maximum production and higher value addition to outputs. Labor productivity is crucial and has implications for strong economic growth and welfare. In their study on Kenya's labor productivity and its determinants in the manufacturing sector, Heshmati and Rashidghalam (2018) found that capital intensity and wages significantly and positively affected labor productivity. They also found that better training and higher education yielded better labor productivity while female share of the labor force reduced labor productivity.

Haouas and Yagoubi (2004) explained that an extensive use of human capital was inefficient compared to partially used technical infrastructure and they found that less efficient industries were expected to adjust faster than the efficient ones. This means that industries closest to the labor requirement frontier have a lower speed of adjustment after liberalization as compared to industries that are further away from the frontier. These authors studied the chemical and mechanical industry in Tunisia, and found that labor and capital had a negative correlation. Haouas et al. (2003) define labor use efficiency as the ratio of actual to optimal employment meaning that those having a ratio greater than one means they are over-using labor for a given level of output produced using optimal production technology.

Regarding factor complementarity and substitutability of labor with other factors such as capital, energy, and maintenance and repairing, Lachmann (1947) found that factor input variables complemented a production plan and played a role in the production process. While he saw substitution as a phenomenon of changing needs which arose when the existing plan went wrong. This means that without changing the final output, a factor can turn into an element of an existing plan. Both have their own importance and Lachmann (1947) underlined that substitutability focused on the same output with a different combination of factors while complementarity depended on the 'technical rigidity' in changing the output than in the factor of production. Hence, the existing combination of inputs was used for producing a different output.

Sectoral differences in the degree of capital-labor substitutability have also been analyzed by Mućk (2017) who found that sectors having higher elasticity of substitution between capital and labor enjoyed more advantages of changing. In other words, when the wage to rental rate ratio changed, the more flexible the sector the better as compared to being less flexible. As the growth rates of sectoral capital-labor ratios varied and their share of each factor can move in different directions, Mućk (2017) concluded that capital-labor ratios were the driving force in structural changes as they saw structural changes push out United States from the agriculture sector. Sector level structural changes can also be applied to the air transport sector through introducing advanced new technologies which contribute to capital, energy, and maintenance and repairing increasing and as a consequence the share of productive labor shrinking to a certain level.

3. Data and a description of the variables

This study uses balanced panel data of 13 Ethiopian airports covering a period of 16 years (2002-17) with 208 observations. Airports that had data for a long period and had been providing services for long years were selected for the study. For a complete understanding of this study, the geographical locations of the airports are also provided. Geographically all the selected 13 domestic and international airports are located throughout the country. The Addis Ababa International Airport, which is a hub for Ethiopian airports and the Horn of Africa, is located in the capital city. Others like Mekelle International Airport and Axum Domestic Airport are located in the Northern part of Ethiopia in the Tigrai regional state. The Gonder Domestic, Bahirdar International, and Lalibela Domestic Airport are also in the Northern part of Ethiopia specifically in the Amhara regional state.

Dire Dawa International, Jijiga Domestic, and Gode Domestic Airports are in the Dire Dawa administrative council and Somali regional state respectively, both are located in the Eastern part of the country. In the Southern part of Ethiopia there are Arbaminch and Jimma domestic airports. They are located in the Southern Nations and Nationalities People of Ethiopia and Oromiya regional states respectively while in the Western part of Ethiopia there are Gambella and Assosa domestic airports which are located in Gambella and Benshangul Gumiz regional states respectively.

The data for these airports is compiled in such way that finance related data is extracted from their final annual external audit reports, whereas human resource data systems are the main data source for labor force numbers and working hours. Passenger and freight cargo data is collected from the statistics departments of Ethiopian airports. The dependent variable is measured by the total employment (L) of each airport's effective working hours excluding weekends, annual leave, and holidays. The model's independent variables are average wage (W), workload unit of passenger (Yp) and freight cargo (Yc) transported as aggregate output per year (Y), capital investments (K) per labor hour, energy use (E) per labor hour and maintenance and repairing M) services per labor hour. All data captures annual information and is considered per year.

3.1 Output data's definitions

Airport services have a multi-output and multi-input nature. Literature refers to the number of passengers transported, air traffic movements (Ya), and cargo transported in kg as the aviation industry's output variables. This research uses passengers transported (Yp) and freight cargo (Yc) as outputs produced by the airports every year. As service rendering public enterprises, revenue generation is the core business of the airports. The most prominent means of generating revenue are related to airports' outputs like aircraft movements, passenger movements, and freight cargo transportation. Airports collect reasonable service charges when an aircraft uses the runway, taxiway, apron, and aircraft support from ground handling activities. Besides, a significant amount of revenue is also collected from non-aeronautical activities such as duty-free shops, food and beverage outlets, special lounges, parking services, and others.

3.2 Input data's definitions

Capital input

Airports have different types of fixed and variable inputs. Almost all capital inputs (K) are categorized as fixed inputs, for example, the number of passenger terminal buildings with various facilities and equipment such as check-in counters, baggage handling systems, number of boarding gates, and passenger boarding bridges. Aircraft movement areas such as the number of runways, taxiways, and the apron area are also considered capital inputs. The rest of the capital inputs are sub-stations or power houses with standby generators including electrical and system networking.

Labor inputs

Aircraft and passenger movements at airports are managed by a qualified and experienced workforce. When an aircraft lands and takes off, the runway lighting, taxiway, and guidance in the apron area require expertise. Besides in all terminal building there are airport passenger customer handlers. Highly sophisticated airport special systems, networking, and electric systems are used for this. In this study labor hour (L) is used as one of the dependent variables.

Energy inputs

An interrupted energy input (E) measured in terms of lighting and fuel consumption is very critical for all airports. Communication between the terminal, tower, and aircraft can only be smooth if there is an uninterrupted power connection between and among all systems, facilities, and airport equipment including fire trucks.

Maintenance and repairing

In addition to the terminal building, runway/taxiway, and the apron area's maintenance and repairing, facilities such as lifts, escalators, power house, data room, data centers, and the entire system and networking need regular maintenance and repairing (M) services.

In general, the data source of this study is annual records of Ethiopian airports. The sample includes 13 airports and the data is balanced panel data covering the period 2002-17; 208 observations are used for the analysis. The labor use frontiers were fitted for one aggregate output and three inputs. Important variables of inputs and the outputs are described in Table 3.1. Monetary variables are in fixed 2009 prices.

Table 3.1. Summary statistics of the data (2002-17), (NT= 208 observations)

Variable	Descriptions per year	Mean	Std. Dev.	Min.	Max.	CV
L	Man-day productive hours of effective labor force	96,188.08	139,751.30	5,040	756,000	1.45
Yp	Annual passenger movements converted to kilogram (kg '000' not cv)	40,900	143,000	119.70	1,020,000	3.49
Yc	Air freight cargo transported per year in kilogram (1,000kg)	11,400	40,400	0.001	243,000	3.53
Y	Aggregate passengers and freight cargo outputs (kg '000 without cv)	52,300.	178,000	120.691	1,260,000	3.40
Ya	Annul aircraft movements	6,891.18	16,623.63	222	111,201.6	2.41
K	Capital investments per effective labor hour	3,284.52	4,790.513	65.20	30,162.85	1.43
M	Maintenance and repairing expense per labor hour	19.93	25.22	0.12	165.85	1.27
W	Average wage	47,580.31	18,440.11	2,714.62	14,8704.1	0.39
E	Energy per labor hour	3.64	2.25	0.71	12.57	0.62

Source: Author's calculations using data from Ethiopian Airports (2018).

Table 3.1 summarizes the important variables of the study. In this study man-day productive labor hours (L) is the dependent variable while annual passenger movements converted into kg equivalent (Yp) and annual air freight cargo transported in kg (Yc) are the output variables. Capital investments per effective labor force (K), average wages (W), and energy consumption per effective labor hour (E) are input or independent explanatory variables in this study. Other variables such as maintenance and repairing expenses per labor (M) and annual aircraft movements (Ya) are additional explanatory variables for inputs and outputs. Since their estimation results were not statistically significant, the study excludes them from the analysis but due to their importance their trends are given in Table 3.1.

As shown in Table 3.1, output value of passengers converted into kg was on average 40.9 million kg as the passengers' share and 11.4 million kg of cargo freight. When comparing airports, the smallest airport transported 119,700 kg and had a zero cargo share while the biggest airport reached more than 1 trillion kg equivalent of passenger share and 243 million kg of freight cargo. As Table 3.1 shows, a statistical analysis of the kg share of passengers, man-day productive hours of labor, aircraft movements, and kg of freight cargo including average wages per year have very high variations between the minimum and the maximum values. Similarly, the value of the standard deviation is very high compared to the mean of production. This shows the existence of extreme variations between airports and significant growth within airports across the study period.

The coefficient of variation that defines the ratio of standard deviation to the mean of the variables which is also given in Table 3.1 is higher in passenger movements and freight cargo transported implying that the greater the level of dispersion around the mean, the higher the capacity and utilization differences among airports. On the other hand, average wages and energy per productive labor hour (0.62) had lower CV values. According to the definition of the coefficient of variation the lower the value of CV, the more precise the estimate.

A statistical analysis of the other inputs per labor hour is given in Table 3.1. Average wages of airport employees are also given in this table. The mean wage per worker per airport was 47,580 Birr per annum which is the same as 3,965 Birr or nearly 4,000 Birr per month per worker with a standard deviation of 18,440 Birr showing significant variability among airports as well as among workers. Similarly, the mean of capital investments per labor hour was about 3,284.50 Birr with a minimum value of 65.20 and a maximum value of 30,162.85 Birr per labor hour. This is extreme variability and is proved by a standard deviation of 4,790.5 Birr per year which is more than the mean value. Lastly, the mean man-day productive hours of effective labor (L) was 96.188 hours. The minimum labor hours per airport were 5,040 while the maximum working hours per airport were 756,000. Such extreme variability is often related to big variations in aircraft and passenger movements in the respective airports.

4. The empirical input requirement frontier model

This section presents the stages involved in developing the input requirement efficiency function, production possibility frontier, input requirement function, and the stochastic input requirement frontier. Production is a process that represents a transformation of inputs into outputs while production function is described as a transformation process with mathematical representation of inputs into outputs (Kumbhakar and Wang, 2010). Assuming one output (Y) and many inputs (X) the production function can be given as:

(3.1) $Y = f(X, t)$

Hence, the function $f(.)$ is specifying the technology governing the input-output relationship.

Assuming that a production possibility frontier (PPF) has two outputs and multi-inputs, Kumbhakar and Hjalmarsson (1998) formulated the PPF model as:

(3.2) $f(X_J, t, Y_m) = 0$

where X and Y are vectors of inputs and outputs, t is the time variable representing technology, and other inputs may be specified depending on the technology requirements.

The labor input requirement function is defined as the relationship in the production frontier that minimizes use of labor with a given amount of output and technology. Kumbhakar and Hjalmarsson (1995) describe the general framework of labor use production function as:

(3.3) $L = f(X, Y, t)$

Equation (3.3) defines the relationship of the production frontier given the amount of L where L is labor used in the production process, Y are outputs (services) produced using the labor and other X inputs. The most common inputs are capital, energy, materials, and t representing technology.

As explained by Rashidghalam et al. (2016) the stochastic frontier model is directly related to the objective of input minimization for a given output in the production process. Once the production possibility frontier satisfies the regulatory conditions referred to by Kumbhakar and Hjalmarsson (1998), in Diewert's (1974) work, the production technology of the labor requirement frontier or minimum input requirement frontier (cost frontier) can be specified as:

(3.4) $L = f(X, Y, t)\exp(v)$

where v is the random error. We can also rewrite the model incorporating the stochastic frontier and technical inefficiency components (u_i) as:

(3.5) $L = f(X, Y, t)\exp(v + u)$

Here the term $u \geq 0$ indicates a firm's technical inefficiency and v represents the statistical noise that can take both positive and negative values. As usual, inefficiency is measured relative to firms' operating stochastic frontier and obtained by setting $u = 0$.

Battese et al. (2000) investigated the labor use model in the Swedish banking industry. In this model, the total quantity of labor used in hours per year was the dependent variable while total public loans, maximum guarantees, deposits, number of branches, value of inventories, and year of observations were also considered in the translog stochastic frontier analysis. The v_{it} random variable associated with measurement errors in the labor variable or misspecification of the explanatory variables was assumed to be independent and identically distributed with $N(0, \sigma_v^2)$ distribution, independent of $\mu_{it}s$.

Assume an industry is using more labor than other necessary factors of inputs for producing a given level of output. According to Haouas et al. (2003) such an assumption is possible any time. It can happen due to variations in demand for goods produced, performance level, degree of capacity utilization, and slow market conditions. Despite this, firms operate with the objective of minimizing labor inputs for producing a given level of output. Haouas et al. (2004) explain that there is also a labor requirement frontier which is a potential target for any rational labor minimizing firm.

For simplicity, let the minimum target level of labor be denoted by L_0^* and the actual level by L once it is assumed that labor is the only variable input considered for the production of output Y. Here two possible scenarios are worth mentioning. The first one is if $L > L_0^*$, as this means an overuse of labor or the amount of labor input used is more than the minimum required which is clearly an indication of employment inefficiency. The second concern is if both are equal $L = L_0^*$, in this case it is assumed that employers are using the labor efficiently and the actual labor employment is close to the labor requirement frontier.

Estimating labor use efficiency is done assuming a parametric functional form $f(x)$. An estimation of the model starts with a parametric estimation of the frontier and then estimating the degree of inefficiency. According to Kumbhakar and Wang (2010) the various methods of estimation and the choice of method depend on whether distributional assumptions of the error components are preferred or it is assumed without any distributional assumption for the error components (distribution free approach). The third approach is using very specific distributional assumptions of the error components and applying the maximum likelihood (ML) method using the stochastic frontier approach. Besides, there are a number of approaches that lie between these two extremes. This study focuses on the maximum likelihood method with a distribution free approach.

5. Panel data labor use model's specification and estimation

Assume that the labor productive hour requirement function of Ethiopian airports can be represented as in Equation (3.5). The inverted factor demand or labor use is specified as a function of different services produced, capital intensity, energy, material use, and technology. Diewert (1974) was the first to introduce the inverted functional relationship of the input requirement function.

The productive labor hour function specified earlier captures the amount of labor hours necessary for producing a given level of service outputs. In line with the model given in Heshmati and Haouas (2011), the input requirement function shows that the level of productive hours depends on the production technology $f(.)$, technical inefficiency (u), and other random factors that could have positive and negative impacts on service provision (v). Accordingly, the productive labor hour's model includes the expected random error terms, the inefficiency effect of deploying labor across airports, and a random shock.

In the stochastic frontier model developed by Aigner et al. (1977), u is one sided and $u \geq 0$. This means that if the actual productive labor hours are equal to the minimum required amount of productive labor hours, then $u = 0$, and the airport industry is 100 percent efficient in the use of productive labor hours. This also shows that the results from Equation (3.4) will be a standard productive labor hour function. So, a value close to zero shows that productive labor hours are technically efficient.

Pitt and Lee (1981) introduced the generalized approach of the panel data model that can handle cross-sectional and time series data which is also applicable to the input requirement function. Schmidt and Sickles (1984) made a distinction and advanced the model to use it for panel data.

The Cobb-Douglas panel data form of the productive labor hours input requirement function in logarithm form is written as:

$$(3.6) \quad \ln L_{it} = \alpha_0 + \beta_1 \ln W_{it} + \beta_2 \ln Y_{it} + \beta_3 \ln K_{it} + \beta_4 \ln E_{it} + \beta_t t + \varepsilon_{it}$$

$$i = 1,2......, N \quad t = 1,2......, T$$

where i represents the i^{th} airport unit, t^{th} time period, $\ln L_{it}$ is log of productive labor hours, $\ln W_{it}$ is log of average real wages, $\ln Y_{it}$ is log of aggregate output of passenger and freight cargo workload unit, $\ln K_{it}$ is log of capital per productive labor hour, $\ln E_{it}$ is log of energy consumption per productive labor hour, and ε_{it} is the error term. Capital in this model is long-term capital investments represented by the values of the fixed assets. Each airport's energy consumption is the sum of its total fuel and light consumption. The next is decomposing the deviation from the input requirement frontier into statistical noise (v_{it}) and technical inefficiency (u_{it}) components, that is, $\varepsilon_{it} = v_{it} + u_{it}$.

Various models have been developed based on different assumptions of inefficacy. This study uses the labor use efficiency of the panel data stochastic frontier model's estimation processes following three models: the fixed-effects model, KH-1995 model, and the MLE approach.

Model 1: Time-invariant fixed-effects model

This is the first of the three inefficiency models used in this study which is assumed to be time-invariant and individual-specific under the fixed-effects (FE) framework model. In this model an estimation can be done without distributional assumptions. According to Schmidt and Sickles (1984) the time-invariant fixed-effects model is similar to the standard FE panel data estimation model. They applied the standard estimation method for estimating the parameter of the model. According to Parmeter and Kumbhakar (2014) the standard FE panel data model can provide consistent estimates of β though $\hat{\alpha}_i$ is a biased estimator of u_i. By construction, $u_i > 0$ by construction and the individual effect α_i is treated as fixed and unobserved individual effects.

In the fixed-effects approach, u_i is allowed to correlate with x_{it} freely. According to Mundlak (1961) heterogeneity (in this case inefficiency) is believed to be correlated to the inputs under consideration. This is one of the desirable properties of the empirical applications of the model. In contrast to this, the FE approach excludes other time-invariant variable regressors such as region of location from the explanatory variable x_{it} so as to avoid perfect multi-collinearity with α_i (Kumbhakar et al., 2015; Parmeter and Kumbhakar, 2014).

Thus, the ordinary least squares estimation (OLS) of the fixed-effects model includes individual dummies as a regressor for α_i which we call the least square dummy variable (LSDV) method where the coefficient of the dummies are estimates of α_i. All individual firm's cross-sectional units have one fixed effect parameter and the number of dummies to be included in the model is equal to the number of cross-sectional units in the data. This means the $(N+K)x(N+K)$ matrix where N is the number of cross-sectional units and K is the number of regressors' x_{it} variables.

According to Kumbhakar et al. (2014,), Kumbhakar et al. (2015), and Parmeter and Kumbhakar (2014) different approaches can be followed to manage t, the difficulty of the model, before removing α_i which is unobserved individual effects. As a result, if applying the first difference, the and/or within transformation in the panel data model is preferable (either of these can easily eliminate α_i). Hence, the transformed model can be estimated using OLS and the OLS estimator of $\hat{\beta}$ is a consistent estimator from which the values of $\hat{\alpha}_i$ have been recovered from the residual mean of each individual cross-sectional unit. Again $\hat{\alpha}_i$ is obtained using a simple transformation to recover $\hat{u}_i > 0$ that will also be a consistent estimator if $T \to \infty$. Kumbhakar et al. (2017) and Parmeter and Kumbhakar (2014) further elaborate on the panel data time-invariant model in which consistent estimates of β can be obtained through the transformed model as $T \to \infty$. Thus, $\hat{u}_i$ is estimated based on Schmidt and Sickles' (1984) model as:

(3.7) $\hat{u}_i = \hat{\alpha}_i - \min_i\{\hat{\alpha}_i\} \geq 0 \quad i = 1,...,N$

The implicit assumption of this model's formulation is that the most efficient firm/unit in the sample is considered to be 100 percent efficient while the inefficiency estimates in the fixed-effects model are relative to the best firm/unit in the sample. The model is very sensitive to outlier observations forming the frontier reference unit and the inefficiency and heterogeneity effects are confounded. Thus, firm-specific efficiency function can be:

(3.8) $\hat{T}E_i = \exp(-\hat{u}_i) \quad i = 1,...,N$

As stated by Rashidghalam et al. (2016) a limitation of the FE model is the assumption of time-invariant inefficiency. In the FE model, individual heterogeneity and inefficiency are not separated. The core idea of this model is that inefficiency levels do not change over time but may vary across individuals. According to Parmeter and Kumbhakar (2014) and Kumbhakar et al. (2015) the inefficient unit in the fixed-effects (be it firm) never change over time which means that firms do not learn over time. Thus, these inefficiency conditions may be related to the managerial capabilities of the firms during the period. Practically, market competition in the world is so dynamic that such constant and restrictive conditions are unrealistic and changes are expected over time.

Model 2: Time-variant model separating persistent and transitory inefficiency

The distinction between persistent/time-invariant and transient/time-varying components of technical inefficiency were improved simultaneously following Colombi et al. (2014) and Kumbhakar et al. (2014). The underpinning concept is that time-invariant inefficiency is considered as persistent inefficiency which is part of the management style of individual firms and such inefficiency cannot be resolved without changes in the government's policy for the industry. However, despite these facts, the residual component of inefficiency might change over time with the existing management system and without a change in a firm's operations (Kumbhakar and Heshmati, 1995; and Kumbhakar et al., 2014).

In the second model, the labor use efficiency follows Kumbhakar and Heshmati (1995) models is applied including its separation procedure for time-invariant persistent efficiency and time-varying transitory efficiency which is specified as:

(3.9) $\ln L_{it} = \alpha_0 + f(W_{rt}, .Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + v_{it} + (u_i + \tau_{it})$

where the error term ε_{it} is decomposed into $\varepsilon_{it} = v_{it} + u_{it}$. u_{it} is technical inefficiency and v_{it} is the statistical noise. Next is decomposing technical inefficiency into persistent (time-invariant) (u_i) and residual (time-varying) inefficacy (τ_{it}), that is, $u_{it} = u_i + \tau_{it}$. The first is firm-specific while the second component is both firm- and time-specific.

To estimate the model let us rewrite Equation (3.9) as:

(3.10) $\ln L_{it} = \alpha_0 + u_i + f(W_{rt}, .Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + v_{it} + (\tau_{it} - E(\tau_{it}))$

$$\ln L_{it} = \alpha_i + f(W_{rt}, .Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + w_{it}$$

hence, w_{it} has zero mean and constant variance. Equation (3.10) fits the standard panel data model perfectly with firm-specific effects (the one-way error component model), and can be estimated either through the fixed-effects framework or through the random-effects framework. The estimation procedure under the fixed-effects model is a multi-step framework which involves several steps:

Step 1: The standard within transformation estimation model is conducted to remove α_i before estimation. Then the within transformed w_{it} will generate a random variable that has zero mean and constant variance. After this OLS can be used on the within transformed data to obtain a consistent estimate of β.

Step 2: Estimating u_i based on the minimization of $\hat{u}_i = [\min_i(\hat{\alpha}_i] + \hat{\alpha}_i = \bar{r}_i - \min \bar{r}$, where $\hat{\alpha}_i$ is the ith fixed effect. The formula assumes an estimated value of inefficiency u_i relative to the best airport in the sample used for this study.

Step 3: Once we have obtained β and u_i, we can calculate the residual $e_{it} = y_{it} - x'_{it}\hat{\beta} + u_i$. Here an additional assumption of maximum likelihood can be used to separate v_{it} from τ_{it}.

Step 4: Having removed $\hat{\beta}_0$ from e_{it}, a JLMS conditional mean or median technique can be used for estimating τ_{it}.

In a general estimation under the fixed-effects framework, that is, the estimation of Equation (3.10) using the standard fixed-effects panel data model obtains a consistent estimate of β in step 1. The next step is estimating persistent technical inefficiency, u_i. Step 3, estimates $\hat{\beta}_0$ and the parameter associated with the random components v_{it} and τ_{it}. Finally, the time varying (residual) components of inefficiency τ_{it} are estimated.

Model 3: Maximum Likelihood Estimation method

By imposing the assumption of distribution, the maximum likelihood (ML) model can be estimated on the error terms v_{it} and u_{it}. The model and its error components can be written as:

$$\begin{aligned} &\ln L_{it} = f(W_{it}, Y_{it}, K_{IT}, E_{IT}, M_{it}; \beta) + \varepsilon_{it} \\ (3.11)\quad &\varepsilon_{it} = v_{it} + u_{it} \\ &v_{it} \sim N(0, \sigma_v^2) \\ &u_{it} \sim N^+(0, \sigma_u^2) \end{aligned}$$

Kumbhakar et al. (2015), Filippini and Greene (2016), and Rashidghalam et al. (2016) note that the accuracy of the procedure enables the ML estimation method to generate higher efficiency in its estimation at the cost of strong assumptions of normality of the random error term. Accordingly, the likelihood function for the ith observation of the model is written as:

(3.12) $$\ln L_k = cons + \ln \Phi(\frac{\mu_{k^*}}{\sigma_*}) + \frac{1}{2}\left\{ \frac{\sum_t \varepsilon_{it}^2}{\sigma_v^2} + \left(\frac{\mu}{\sigma_u}\right)^2 - \left(\frac{\mu_{i^*}}{\sigma_u}\right)^2 \right\} - T\ln(\sigma_v) - \ln(\sigma_u) - \ln\Phi\left(\frac{\mu}{\sigma_u}\right)$$

where $\mu_{i^*} = \dfrac{\mu\sigma_v^2 + \sigma_u^2 \sum_t \varepsilon_{it}}{\sigma_v^2 + T\sigma_u^2}$ and $\sigma_* = \dfrac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + T\sigma_u^2}$

(3.13) $$\ln L_{it} = \alpha_0 + f(W_{rt}, Y_{nt}, K_{rt}, E_{rt}; \beta) + \mu_i + v_{it} + \eta_i + u_{it}$$

hence, $\eta_i > 0$ and $u_{it} > 0$ are the two inefficiency (time invariant and time varying) and μ_i and v_{it} are the other two firm heterogeneity effects and random errors respectively.

In this model Kumbhakar et al. (2014) and Heshmati et al. (2016) explain the key multi-step procedure and rearrange Equation (3.9) as:

(3.14) $$\ln L_{it} = \alpha_0^* + f(W_{rt}, Y_{nt}, K_{rt}, E_{rt}; \beta) + \alpha_t + \varepsilon_{it}$$

where $\alpha_0^* = \alpha_0 - E(\eta) - E(u_{it})$; $\alpha_i = \mu - \eta_i + E(\eta)$ and $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$

The general error term ε_{it} is decomposed into $\varepsilon_{it} = v_{it} + u_{it}$, where u_{it} is technical inefficiency and v_{it} is statistical noise.

The log-likelihood function of the MLE model is found by using the summation $\ln L_i$ over i where $i = 1,......,N$. Thus, the unknown parameter of MLE is estimated by using the maximizing log-likelihood function (Greene, 2008; Filippini and Greene, 2016; Colombi et al., 2011; and Kumbhakar et al., 2013). Once the parameter of the model is estimated, inefficiency of each i can be computed from either the mean or the mode based on Kumbhakar et al.'s (2015) estimation techniques and procedure.

Similarly, the value of α_i and ε_{it} have zero mean and constant variance random variables. As a result, Equation (3.14) can be estimated in three steps:

- The first step estimates $\hat{\beta}$ by using the maximum likelihood estimation panel regression approach. This model (Equation 3.14) gives the predicted values of $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$.

- Step two follows time-varying technical inefficiency u_{it} of step one and is estimated using the predicted values of $\hat{\varepsilon}_{it}$. The model specification in the second step is:

(3.15) $\varepsilon_{it} = v_{it} + u_{it} + E(u_{it})$

assume v_{it} is i.i.d. $N^{+}\left[0, \sigma_v^2\right]$ and u_{it} is i.i.d. $N^{+}\left[\mu, \sigma_u^2\right]$ that produces $E(u_{it}) = \sqrt{(2/\pi)}\sigma_u$. This means disregarding the changes between the true and predicted values of ε_{it} is a common practice for any two or more procedures. Thus, Equation (3.14) can be estimated using the standard SF technique. Kumbhakar et al. (2015) referred to Battese and Coelli (1995) and Jondrow et al. (1982) this process produced the prediction of time-varying residual technical inefficiency component u_{it} that using $\exp(-u_{it} / \varepsilon_{it})$.

- The final step is estimating Equation (3.13) in terms of η_i which is done following a similar procedure as in step two and applying the best linear predictor of α_i from step one. The model is:

(3.15) $\alpha_i = \mu_i - \eta_i + E(\eta_i)$

thus, μ_{it} is assuming i.i.d. $N^{+}\left[0, \sigma_\mu^2\right]$ and η_i is i.i.d. $N^{+}\left[0, \sigma_\eta^2\right]$ produces $E(\eta_{it}) = \sqrt{(2/\pi)}\sigma_\eta$.

As indicated in this procedure, we can estimate persistent technical efficiency from $PTE = \exp(\eta_i)$ where $\hat{\eta}_i$ is the JLMS estimator of η_i; hence, the overall technical efficiency (OTE), is found from the product of PTE and RTE, that is, $OTE = PTExRTE$.

6. A Discussion of the results

An analysis of labor use efficiency of Ethiopian airports focused on the specifications and estimation of a stochastic frontier panel data approach for 13 international and domestic airports covering the period 2002-17. The main variable of the study is productive labor hours as the dependent and focus variable of the study. Workload unit of passenger and freight cargo transported is output in this study. The other important variables are average wages, capital investments, maintenance and repairing and energy consumption per productive labor hour.

The econometric model's specification and selection show that the translog functional form did not have the required convergence and its estimation output was not meaningful for an interpretation. Hence, the translog functional form for a labor use efficiency analysis was not applicable. Thus, the study focused on the Cobb-Douglas labor use input requirement function. This model was also tested for the suitability of all the basic assumptions of the Cobb-Douglas stochastic frontier approach labor use input requirements. The LR test of the model's specification was satisfied which helped to continue proceed with the panel data labor use input requirement stochastic frontier.

The next step was determining the selection of the fixed-effects versus random-effects model for which the Hausman test was done. The chi-square distribution with 6 degrees of confidence was 73.86 while the tabulated chi2 critical value at the 5 percent level of significance was 11.07. In addition, the probability of the p-value of chi2 was also (0.000). Hence, the null hypothesis of no systematic difference was rejected and the model was found in favor of the fixed-effects model. Thus, the fixed-effects model of time-invariant and time-varying panel data labor use input requirement was the preferred method. In addition to the fixed-effects model, maximum likelihood estimation (MLE) techniques and multi-step alternative approach of the inefficiency effect were also applied to increase the efficiency of the estimation process.

In this study endogeneity was not treated separately and by assuming a fixed-effects procedure it was able to control for unobserved sources of endogeneity that are airport specific (to some extent). Including time trend in the fixed-effects model was also assumed to further remove the unobserved time effects. One advantage of the panel data analysis is controlling the endogeneity problems by transforming the variable that is differencing and demeaning.

6.1 Fixed-effects model's estimation

In this labor use efficiency analysis, the time-invariant fixed-effects model (Model 1) was estimated and the estimation results are presented in Table 3.2. Overall, the model has a statistically significant power in explaining variations in the dependent variable, lnL. This is demonstrated by the statistical significance of the F-statistics which indicates that the regression coefficients are jointly significant. The explanatory variables considered in the labor use requirement model (lnL) are work load unit of passenger and freight cargo (lnY), average wages (lnW), capital per productive labor hour (lnK), maintenance and repairing per productive labor hour (lnM), energy per productive labor hour (lnE), and time trend representing technology or shift in the labor use function over time. Among these variables workload unit of passenger and freight cargo (lnY), energy consumption per productive labor hour (lnE), and annual technical change (yr) had statistically significant parameter estimates. These parameters can be interpreted as elasticities of a percentage change in lnL in response to a percentage change in the determinants of labor use.

Table 3.2. Estimation of Labor use the time invariant fixed-effects model

Explanatory variables	Coef.	Std. Err	p>|t|	95% Confidence Interval	
Logarithm of aggregate passenger and air-freight cargo output (lnY)	0.0564**	0.026	2.16	0.005	0.1079
Logarithm of average wages (lnW)	-0.049	0.050	-0.98	-0.147	0.0497
Logarithm of capital investments per effective labor hours(lnK)	-0.013	0.021	0.61	-0.029	0.0550
Logarithm of energy per productive labor hour (lnE)	-0.123**	0.051	-2.42	-0.224	-0.0229
Logarithm of maintenance per productive labor hour (lnM)	-0.037	0.034	-1.09	-0.104	0.0298
Time trend (yr)	0.071***	.007	9.14	0.055	0.0857
Constant	-131.14***	15.36	-8.54	-161.44	-100.84
R2 adjusted	95.62%				
Corr(u_i, Xb) = 0.1118, F(6,188) = 121.95, Prob > F = 0.0000					
F-test that all u_i = 0: F(12, 188) = 89.76 Prob > F = 0.0000					

Note: ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level respectively.

Source: Author's calculations (2019).

The estimation results of a workload unit of passenger and freight cargo shows that every 1 percent increase in output services (passengers and freight cargo) was highly related to a 0.0564 percentage increase in the productive labor units. The estimated coefficient of energy consumption per productive labor hour (lnE) showed that other things being constant, a 1 percentage point change in lnE was associated with a -0.123 percentage point change in the labor use in the opposite direction. Since -0.123 is less than one in absolute value, a 1 percentage change in energy consumption will affect productive labor by less than 1 percentage down. This is an indication that productive labor experienced decreasing returns to scale. Though the response is still low and inelastic, the direction of the association has flipped. This result means that high energy consumption per productive labor hour (lnE) reduced the quantity of productive labor hour inputs used. If lnE is positive, energy per productive labor hour and productive labor are complementary whereas a negative energy coefficient suggests that labor and energy are substitutes. This shows that an increase in high-tech airport facilities and systems that require uninterrupted energy which can replace human resources' deployment.

In the time invariant fixed-effects model the coefficient of the time trend yr (0.071) is also positive and statistically significant. Thus, given everything else, the technical progress of labor use increased over time on average by 7.1 percent per annum across at all the airports given aggregated passenger and freight cargo outputs and wage levels with capital, energy, and maintenance and repairing expense per labor hour productivity during the period 2002-17.

The average wage coefficient parameter (W) is negative with the expected sign (as wages increase the quantity of labor decreases) but not significant because the margin of error of the coefficient of average wages is higher than 10 percent and the labor use input of productive hours is not responsive to a change in the value of average wages.

Further, the mean efficiency levels of all the airports was also estimated and is summarized in Table 3.3.

Table 3.3. Summary of Labor use efficiency of the fixed-effects estimation (208 observations)

Variables	Mean (%)	Std. Dev.	Minimum (%)	Maximum (%)
Efficiency of Fixed-effects	47.53	0.32	3.91	100.00

Note: Author's calculations (2019).

The labor use technical efficiency level in the time-invariant fixed-effects estimation's results without a distributional assumption is estimated to be about 47.53 percent on average during the period 2002-17. In other words, airports' inefficiency levels of labor use on average were 52.47 percent higher than the required productive labor hours during the study period. The basic assumption of this model is that technical inefficiency is individual-specific and time-invariant, that is, technical efficiency varies across airports but is constant over time. The variations in the airports range between 4 percent and 100 percent showing that some airport were up to 96 percent inefficient or used 96 percent higher labor than the minimum required labor use (see Table 3.3). The results of the standard deviation also show the existence of extreme variations in efficiency among airports. In this model, the time effect is undermined and this model can only work if the airport's management is not learning from its previous inefficiency.

6.2 Model separating Labor use persistent and transitory inefficiency components

In this section, a separation of time-invariant persistent inefficiency and time-varying technical inefficiency (Model 2) is analyzed based on Kumbhakar and Heshmati's (1995) model. The separation requires a multi-step procedure which was estimated to obtain consistent estimates of the coefficients as shown in Table 3.4. The estimation results of labor use (lnL) as explained by work load units of passenger and air freight cargo (lnY), average wages, capital per productive labor hour(lnK), energy per productive labor hour (lnE), and maintenance and repairing per productive labor hour (lnM) are jointly significant (see F-test, Table 3.4). With the exception of average wages almost all the other coefficients were statistically significant at the 1 percent level of significance. These four significant coefficients can be interpreted as elasticities of a percentage change in labor hours (lnL) in response to a 1 percentage change in either of the four explanatory variables. The elasticities are explained further later.

Taking the output variable, for instance, implies that every 1 percentage point change in the workload unit of aggregate passenger and air-freight cargo output (lnY), ceteris paribus, was highly associated with a 0.1662 percentage point change in labor use (lnL) in the same direction with a relatively inelastic response. Since the coefficient of the output value is less than one, a percentage change in output will affect productive labor by less than 1 percentage upwards and it has decreasing returns to scale. This significant relationship shows that if the production of an output is labor intensive, more labor hours are required to produce the output service for many passengers and air freight cargo.

Similarly, the strong significant levels (1 percent) of capital, energy, and maintenance and repairing show that all other things being equal, a 1 percentage point change in capital investments (lnK) is directly related to a -0.0714 percentage point change in productive labor use with a highly inelastic response. In other words, since the absolute value of the elasticities is less than one, a 1 percent increase in capital will decrease productive labor use by less than 1 percent in the opposite direction with decreasing returns to scale. This shows that labor and capital are substitutable for producing the same level of passenger and freight cargo output. This is consistent with Lachmann's (1947) explanation that substitutability focuses on producing the same output with a different combination of factors while complementarity depends on the 'technical rigidity' in changing the outputs than the factors of production. In addition, Paul (2019) maintains that capital and labor are predominantly characterized by complementarity. This is a paradox as capital accumulation acts as driver of the labor's income share that means capital and labor can be substitutes. Finally, Mućk (2017) found that sectors had higher elasticity of substitution between capital and labor and concluded that capital-labor ratios were a driving force in structural changes.

In the same way, other things being equal, every 1 percentage point change in energy per productive labor hour (lnE) is directly related to a -0.2648 percentage point change in the productive labor hour input use in the opposite direction with decreasing returns to scale. The other significant coefficient of the model is maintenance and repairing per productive labor hour (lnM). All other things being constant, a 1 percentage point change in maintenance and repairing is directly related to a -0.1715 percentage point change in the productive labor hours with decreasing returns to scale. The total coefficient value of the explanatory variables is -0.3878 which is still inelastic and less than unity implying decreasing returns to scale.

Table 3.4. Estimation of Labor use results based on Kumbhakar and Heshmati's (1995) (Model 2)

Explanatory variables	Coef.	Std. Err.	p>|t|	95% conf. interval	
Logarithmic form of aggregate passenger and air-freight cargo output (lnY)	0.1662***	0.028	5.97	0.111	0.221
Logarithmic form of average wages (lnW)	-0.0345	0.059	0.59	-0.081	0.151
Logarithmic form of capital investments per effective labor hour(lnK)	-0.0714***	0.023	-3.30	-0.117	0.026
Logarithmic form of energy per productive labor hour (lnE)	-0.2648***	0.058	-4.54	-0.380	-0.149
Logarithm of maintenance repairing per productive labor hour (lnM)	-0.1715***	0.037	-4.67	-0.244	-0.099
Constant	9.135***	0. 711	12.84	7.73	10.54
Rho (R2)	90.83%				
Corr(u_i, Xb) = 0.3164, F(5,189) = 90.24	Prob > F = 0.0000				
F-test that all u_i=0: F(12, 189) = 58.52	Prob > F = 0.0000				

Note: ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level respectively.

Source: Author's calculations (2019).

In general, one can hypothesize that the production input of capital per productive labor hour (lnK), energy per productive labor hour (lnE), and maintenance and repairing per productive labor (lnM) are highly related and influence productive labor use. According to this model and its results new expansion in airports' infrastructure, additional facilities and system development, and proper coordination and integration of multi-system services contributes not only to an increase in output services but also reduces the quantity of the productive labor hours input used. In other words, the negative relationship between productive labor hours and capital, energy, and maintenance per productive labor hour shows substitutability rather than complementarity in the labor use requirement's functions. This shows that the amount of productive labor hours in the input requirement function have reached saturation. An introduction of a high-tech and self-explanatory system, announcement signages, capital intensive infrastructure, and continuous maintenance of services and facilities have the potential to substitute the additional productive labor hour input and continuing producing passenger and freight cargo outputs.

In the second, third, and fourth steps of the estimation procedure, time-invariant persistent inefficiency and time-varying transitory technical inefficiency were separated according to Kumbhakar and Heshmati's (1995) estimation model. The average mean of technical efficiency and its overall magnitude is given in Table 3.5. The estimated time-invariant technical efficiency level of all airports is 50.67 percent and the mean time-varying residual/transitory efficiency level is 99.87 percent while the combined mean of the product of time-varying and time-invariant technical efficiency is 50.59 percent. In this model, the time-varying technical efficiency level is very high and close to one implying that in the short-run Ethiopian airports' management is practicing proper resource allocations of productive labor hours. Over time, related inefficiency is also temporary and will be recovered as time changes. Hence, the magnitude of transitory inefficiency of productive labor use efficiency is limited by the current practices of the management.

Table 3.5. Mean efficiency of all airports during the study period based on Model 2 (Kumbhakar and Heshmati, 1995)

Model	Efficiency components	Mean	Std. Err.	Minimum	Maximum
Model 2	Residual	99.85	0.001	99.85	99.86
	Persistent	50.67	0.303	5.11	100.00
	Overall	50.59	0.303	5.10	99.86

Note: Author's calculations (2019).

On the other hand, the mean of persistent and overall technical inefficiency of productive labor hour use based on Kumbhakar and Heshmati's model were 49.33 percent and 49.41 percent respectively during the period 2002-17. In addition, that efficiency levels of Ethiopian airports' productive labor hours both minimum persistent and overall technical efficiency are almost the same 5.11 percent and 5.10 percent respectively. This is a very serious finding that some airports had very high levels of productive labor use persistent inefficiency (94.89 percent) on average during the study period. This high level of persistent inefficiency is related to the management and other unobservable firm effects. Hence, without government interventions in the management of Ethiopian airports, persistent inefficiency will not change.

In contrast, some airports have high persistent efficiency (up to 100 percent). In reality, most Ethiopian airports are managing and administering their services following low and traditional ways of management and with the same airport leadership policies. An efficiency analysis was conducted for the low performing airports but the panel data used is annual aggregate which could have an aggregate data effect. Accordingly, in the relative analysis some airports could reach saturation point from the perspective of productive labor use efficiency. In other words, the technical efficiency of productive labor hours could have reached the minimum input requirement level given the output and all other factors of production per productive labor hour. Efficiency improvements in such a situation require government interventions for putting in place a new system, a new policy, and a new management philosophy for the airport industry as this will also lead to the overall economic transformation of the national economy. Economic growth will increase demand for air transport in general and airport services in particular, after which distinctions can be made in efficiency types and magnitude in productive labor use as airports grow over time.

Kumbhakar and Heshmati's (1995) model separates time-invariant persistent inefficiency and time-varying inefficiency. The model underlines that persistent inefficiencies are time-invariant and cannot be reduced without government interventions in changing policy and the strategic management of airports. Considering all time-invariant inefficiency as persistent inefficiency and the presence of unobserved firm effects leads to an upward biased persistent inefficiency (Parmeter and Kumbhakar, 2014). Even though time-invariant firm heterogeneity and time-invariant variables are specified as persistent, this model is still preferable for decomposing technical inefficiency as compared to the fixed-effects time-invariant, true fixed-effects, and true random-effects models (Greene, 2005a, 2005b) and the technical inefficiency distance function (Battese and Coelli, 1995) among others.

6.3 An Analysis of the results of the MLE estimation model (Model 3)

The maximum likelihood approach is the third model used for estimating labor use efficiency of Ethiopian airports. Table 3.6 shows that the overall estimation in the model has a statistically significant power in explaining the labor use dependent variable, (lnL). This can be verified by the statistical significance of the F-statistics where the observed model and parameter estimates are jointly significant. Even though the MLE technique generates higher efficiency, this model also requires a strong assumption of normality. Thus, it is supported by the robustness test statistics in Tables 3.8 and 3.9.

Among these explanatory variables the workload unit of passenger and freight cargo (lnY), capital investments per productive labor hour (lnK), energy consumption values per productive labor hour, (lnE) and maintenance and repairing per productive labor hour (lnM) have statistically significant estimates. In this model, four coefficients can be interpreted as elasticities of a percentage change in lnL in response to a 1 percentage change in either of the four significant variables. Accordingly, a 1 percentage point change in the workload unit of passenger and freight cargo (lnY), ceteris paribus, brings about a 0.1849 percentage point change in productive labor use (lnL) in the same direction with decreasing returns to scale.

Table 3.6. Labor use estimation results using the MLE approach

Explanatory variables	Coef.	Std. Err.	z	[95% Confidence	interval]
Log of aggregate passenger and air-freight cargo output (lnY)	0.1849***	0.0284	6.50	0.1291	0.2407
Log of average wages (lnW)	-0.0562	0.0551	1.02	-0.0518	0.1642
Log of capital investments per productive labor hour (lnK)	-0.0678 ***	0.0230	-2.94	-0.1129	-0.0226
Log of energy per productive labor hour (lnE)	-0.2585***	0.0604	-4.28	-0.3768	-0.1401
Log of maintenance and repairing per productive labor hour (lnM)	-0.1315***	0.0383	-3.43	-0.2065	-0.0564
Constant	8.510***	0.6798	12.52	7.178	9.843
R2 adjusted	88.98%				
LR chi2(5) = 234.64 Log likelihood = -55.108 Prob > chi2 = 0.0000					
LR test of sigma_u = 0: chibar2(01) = 236.38 Prob >= chibar2 = 0.000					

Note: ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels respectively.

Source: Author's calculations (2019).

The coefficient of capital investments per productive labor hour (lnK) shows that, other things being constant, a 1 percentage point change in lnK is associated with a -0.0678 percent change in labor use productive hours (lnL). According to this result, an additional capital investment per productive labor hour (lnK) will result in a reduction in the quantity of productive labor hour deployed. This also shows that there is the possibility of substitutability of capital and labor in this MLE model.

The coefficient of energy cost per productive labor hour (lnE) shows that every 1 percentage point change in lnE is highly associated with a -0.2585 percent change in labor use productive hours (lnL), ceteris paribus. This implies that higher energy cost consumption per productive labor hour (lnE) will result in a significant reduction in the quantity of the productive labor hour input used. Since lnE is negative, energy per productive labor hour and productive labor are substitutes to a certain extent in output production. Similarly, maintenance and repairing per productive labor hour also implies that a 1 percent change in lnM is highly related to a 0.1315 percent change in the productive labor hour input used, other things held constant. Hence, uninterrupted maintenance and repairing of airport infrastructure, facilities, systems, and services can substitute productive labor use at a certain level of producing the output services. The last parameter coefficient is average wage (lnW) which is negative as expected but it is statistically insignificant. Since the margin of error that directly associated with the coefficient of average wage value is greater than 10 percent, the dependent variable labor use productive hours was not responsive to a change in the average wage rates.

Table 3.7. Mean Labor use efficiency of all airports over the study period (%, MLE, Model 3)

Model	Efficiency components	Mean	Std. Dev.	Minimum	Maximum
Model 3	MLE-Residual	99.90	0.0006	99.90	99.91
	MLE-Persistent	49.65	0.2963	5.89	100.00
	MLE-Overall	49.60	0.2959	5.88	99.90

Note: Author's calculations (2019).

The summarized mean results of the MLE approach are given in Table 3.7. The estimation results show that the mean time-varying residual efficiency level of all airports was 99.90 percent while the mean time-invariant persistent and overall efficiency was 49.65 percent and 49.60 percent respectively. Thus, the overall actual labor use efficiency of Ethiopian airports was approximately 49.60 percent which is 50.40 percent higher than the minimum required productive labor hours implying that persistent efficiency is very low and overuse of labor will continue unless some policy or interventions alleviate the inefficiency conditions at airports. Besides, efficiency varied across airports and the benchmarking airports scored more than 99 percent while the persistent efficiency levels of least efficient airports scored as low as 5.89 percent which is 94.11 percent higher than the minimum required productive labor hour deployed. This is extremely serious inefficiency which requires government attention (airports are public enterprises owned by the state). Taking an estimation methodological perspective, Kumbhakar et al. (2017) and Rashidghalam et al. (2016) explain that in terms of the techniques of estimation, MLE has higher efficiency as compared to other efficiency analyses. Hence, the ML estimation's results have relatively higher reliability and leads to conclusion and policy recommendations.

As shown in the estimation results, higher short-run or time-varying transitory efficiency implies that Ethiopian airports are performing properly in allocating short-run resources and any time-varying inefficiency is also easily recovering over time. However, low persistent efficiency which has a permanent effect needs government attention. This high level of persistent efficiency can be on the one hand due to an aggregate data effect even though the dominant assumption of this study comes from overall trends in airports' performance. On the other hand, the current level of these specific airports technical efficiency of productive labor hours reached the minimum input requirements given passenger and air freight cargo output and capital, energy, and maintenance and repairing factors of production per productive labor hour as the inputs. This does not mean that the airports have reached the highest level of efficiency and instead is a relative analysis of reaching saturation. This requires overall productive labor hour use and management in all the Ethiopian airports and an overall economic transformation of the national economy. Improvements in the national economic conditions significantly support air transport growth and stimulate specific airports in particular. This will help airports gain a momentum of growth and efficiency improvements across time and firms.

6.4 Robustness test for the stochastic frontier efficiency models

Since the model specification test improves the efficiency of the model's investigation and the reliability of the estimated output, a thorough model test using the probability of a skewness test for normality was examined. The estimation results of the normality test indicated that the p-value for skewness was strongly significant (0.0004). Thus, the null hypothesis of no skewness is confidently rejected implying that the model is in favor of a left skewed error distribution and it is also verified that the model is properly specified with the Cobb-Douglas labor use function. This took us to the next stage of estimating the stochastic frontier model.

Table 3.8. Skewness/kurtosis tests for normality

Model	Variable	Probability		Joint test	
		skewness	kurtosis	Chi2(2)	Prob>chi2
Maximum likelihood	Err.	0.0000	0.0012	28.85	0.0000
estimation (MLE)	Muf.	0.0000	0.3085	22.65	0.0000

Note: Author's calculations (2019).

Table 3.9. Critical values of the mixed chi-square distribution

Model	Test statistics	Significant level (critical value)			
Maximum likelihood (MLE)	99.675	1	1.642	5.412	9.500

Note: Author's calculations (2019).

As required by the MLE model, the existence of the efficiency model was tested using the log-likelihood ratio (LR) test (Table 3.9). The statistical result of log-LRT is 99.675. Considering a 1 degree of freedom, the critical values of the mixed chi-square distributions are 5.412 and 9.500 respectively at the 1 percent and 0.1 percent significance levels. This means that the null hypothesis of no technical inefficiency is strongly rejected at even the 1 percent level of significance thus proving the existence of technical inefficiency in the model. Thus, once the existence or presence of technical inefficiency is assured, it is possible to analyze the level and condition of labor use technical inefficiency of airports using the stochastic frontier model.

Table 3.10. FE, KH, and MLE mean Labor use efficiency of all airports (2002-17) (208 observations)

ID	Airports	Model 1 FE (%)	Model 2 KH (%)			Model 3 MLE (%)		
		LR-PE	SR-RE	LR-PE	OTE	SR-RE	LR-PE	OTE
1	AABIA	3.91	99.86	5.11	5.10	99.90	5.89	5.88
2	Dire Dawa In'lA	13.54	99.86	19.41	19.38	99.90	19.84	19.82
3	Mekelle In'lA	18.63	99.86	20.29	20.26	99.90	20.56	20.55
4	Bahri-Dar In'lA	18.57	99.86	22.31	22.27	99.90	22.05	22.03
5	Jimma DA	31.17	99.86	36.68	36.63	99.90	35.29	35.26
6	Gonder DA	27.17	99.86	33.96	33.92	99.90	33.21	33.18
7	Axum DA	36.33	99.86	43.65	43.59	99.90	42.83	42.79
8	Lalibella DA	51.90	99.86	58.48	58.39	99.90	55.43	55.38
9	Gambella DA	86.67	99.86	88.88	88.75	99.90	88.63	88.54
10	Arbaminch DA	56.95	99.86	59.51	59.42	99.90	54.96	54.91
11	Gode DA	100.00	99.86	100.00	92.25	99.90	100.00	99.90
12	Assosa DA	86.44	99.86	82.72	99.86	99.90	79.00	78.92
13	Jijiga DA	89.83	99.86	90.74	82.60	99.90	87.67	87.59
	Average	47.52	99.86	50.67	50.59	99.90	49.65	49.60

Note: Author's calculations (2019).

In Table 3.10 the efficiency of the time-invariant approach – the fixed-effects model-- is shown, time-invariant persistent efficiency and time-varying transitory efficiency components were estimated using the Kumbhakar and Heshmati (1995) and MLE models. The estimated average mean technical efficiency of the time-invariant fixed-effects is 47.52 percent while the average mean time-invariant persistent efficiency of Kumbhakar and Heshmati (1995) and the maximum likelihood estimations are 50.67 percent and 49.65 percent respectively. It is known that there is a difference in distributional assumptions and also in the time-varying and time-invariant firm heterogeneity assumptions which leads to different efficiency results. Kumbhakar and Heshmati (1995) and the maximum likelihood estimation models show relative efficiency levels which means that productive labor hour use was 49.33 percent and 50.35 percent inefficient respectively compared to the minimum requirement of labor hours.

Following the estimation of the fixed-effects model, mean efficiency during the study period was also estimated. Assuming an efficient airport is expected to score 100 percent an average mean of 47.52 percent efficiency level implies that there are many airports using productive labor more than the minimum required labor. The mean efficiency score of each airport varied between 3.91 percent at Addis Ababa International Airport and 100 percent at the Gode Domestic Airport. Jijiga Domestic Airport had an efficiency score of 89.83 percent, Gambella Domestic Airport 86.67 percent, and Assosa Domestic Airport 86.44 percent. In contrast, there were also airports with lower efficiency levels during the study period, namely, Dire Dawa International Airport at 13.54 percent, Bahir-Dar International Airport at 18.57 percent, and Mekelle International Airport at 18.63 percent as the second, third, and fourth least efficient airports. Thus, all international airports had lower levels of efficiency implying that their inefficiency was higher than the minimum required productive labor hours. Mean efficiency levels of the time-invariant fixed-effects estimation of the other remaining airports ranged between 27.17 percent for Gonder Domestic Airport and 56.95 percent for Arbaminch Domestic Airport. Such high inefficiency at international airports compared to their domestic counterparts is attributed to higher service quality and capacity requirements.

In Kumbhakar and Heshmati's (1995) advanced model and the MLE approach the residual technical efficiency was separated from the persistent technical efficiency. Using the Kumbhakar and Heshmati's (1995) or multi-step alternative model the highest estimation of long-run persistent technical efficiency among these airports was at Gode Domestic Airport at 100 percent followed by Jijiga Domestic Airport at 90.74 percent, Gambella Domestic Airport at 88.88 percent, and Assosa Domestic Airport at 82.72 percent. The lowest long-run persistent technical efficiency was at Addis Ababa Bole International Airport at 5.11 percent, Dire Dawa International Airport at 19.41

percent, Mekelle International Airport at 20.29 percent, and Bahri Dar International Airport at 22.31 percent. The remaining airports' long-run persistent technical efficiency results ranged between 33.96 percent for Gonder Domestic Airport and Arbaminch Domestic Airport with a 59.51 percent level of efficiency.

On the other hand, the efficiency levels of airports using the MLE model showed significant variations between persistent and transitory efficiency at the airports. In relation to the time-invariant persistent efficiency condition, the relatively better performing airports were Gode Domestic Airport 100 percent, Gambella Domestic Airport 88.63 percent, Jijiga Domestic Airport 87.67 percent, and Assosa Domestic Airport 79.00 percent, while relatively lower performing airports were Addis Ababa International Airport at 5.89 percent efficiency, followed by Dire Dawa International Airport 19.84 percent, Mekelle International Airport 20.56 percent, and B/dar International Airport 22.05 percent respectively. This means that international airports including the national hub Addis Ababa Airport scored the least in labor use efficiency and had excess labor deployment. Their efficiency levels were more than the minimum required productive labor hours.

In the three models, the same airports Gode, Jijiga, Gambella, and Assosa domestic airports scored better in terms of persistent technical efficiency while the other airports Addis Ababa Bole, Dire Dawa, Mekelle, and Bahri-Dar international airports scored lower in persistent technical efficiency. This shows that airports having a larger number of passengers and freight cargo output services scored lower in persistence technical efficiency of productive labor hours. On the other hand, airports having smaller numbers of passengers relative to others had higher persistent technical efficiency of productive labor hours. The relatively low levels of economic activities at these domestic airports and the surrounding region resulted in a limited number of annual passengers being transported. Hence, the time invariant persistent technical efficiency score between 90 percent and 100 percent does not necessary mean that there is no potential for further improvements in efficiency at these airports. Considering the current economic activities of the region and the existing demand, the allocated resource utilization in relation to others has shown better efficiency and will also continue efficient. With overall growth of the economy, additional air transport demand can be created. Following to the demand and passenger capacity the efficiency analysis can be investigated to examine the trend of productive labor hour input requirements.

According to Kumbhakar and Heshmati (1995), Parmeter and Kumbhakar (2014), Kumbhakar et al. (2014), Rashidghalam et al., (2016) and Kumbhakar et al.'s (2017) efficiency analyses time-variant transitory technical inefficiency can change over time while persistent technical inefficiency cannot change over time or across individual firms unless there is an active policy on the management of the firms. Hence, in this study airports with higher persistent inefficiency will continue being inefficient unless the Government makes serious structural policy changes for all airports for achieving the minimum productive labor input requirement levels. This could include revising the employment and labor use efficiency policy for increasing labor productivity for which specific government interventions are needed in the sectoral policy for bringing about structural changes and reducing future inefficiency.

7. Summary, Conclusion, and Recommendations

This chapter focused on labor use efficiency for optimizing the minimum labor requirements which will help to reduce the cost of production for airports service outputs. This study analyzed the labor use efficiency of Ethiopian airports using the panel data stochastic input requirement function with the concept of minimizing labor use in the production of airports' output services. It studied 13 international and domestic airports for analyzing their productive labor hour use efficiency covering the period 2002-17. The model's specifications included productive labor hours as the dependent variable, while the independent variables were workload unit of passenger and freight cargo as output variables, average wages, and capital investments per productive labor hour, maintenance and repairing per productive labor hour, and energy consumption per productive labor hour. Fixed-effects approach of the time-invariant, Kumbhakar and Heshmati (1995) or multi-step alternative, and maximum likelihood estimation (MLE) methods were also applied to enhance the validity of the assumptions and estimating efficiency.

In the time-invariant fixed-effects model, the coefficient passenger and freight cargo, energy per productive labor hour, and the time trend for annual technical productivity (yr) were statistically significant. The results of the variables estimation of passenger and freight cargo (lnY), capital per productive labor(lnK), energy per productive labor (lnE), and maintenance and repairing per productive labor (lnM) were found to be statistically significant in Kumbhakar and Heshmati's (1995) model and in the MLE approach. The negative and statistically significant results of exogenous capital, energy, and maintenance and repairing inputs showed that in the course of providing airport services these inputs also contributed to minimizing labor use more by substituting the role of labor than by complementing it. In other word, the study concluded that labor use and airport output were complementary hence expansion of airport facilities is recommended. Capital, energy, and maintenance and repair inputs substitute labor use.

Labor use technical efficiency level of the time-invariant fixed-effects estimation results without distributional assumptions was estimated to be about 47.52 percent on average during the period 2002-17. The summarized mean average efficiency results of Kumbhakar and Heshmati's (1995) model showed that long run persistent and overall technical efficiency was 50.67 percent and 50.59 percent respectively with a 99.86 percent residual efficiency level. The final and relatively efficient MLE estimation method showed that the time-varying residual efficiency level of all the airports on average was 99.90 percent while the time-invariant persistent and overall efficiency was 49.65 percent and 49.60 percent respectively. Thus, the actual labor use efficiency of Ethiopian airports was approximately 49.60 percent. The average mean labor use technical inefficiency of the time-invariant fixed-effects estimation was 52.48 percent while the average mean time invariant persistent labor use inefficiency of Kumbhakar and Heshmati's (1995) model was 49.33 percent. Finally, the average mean time invariant persistent labor use inefficiency maximum likelihood estimation was 50.40 percent. It is known that there are differences in distributional assumptions and the efficiency results are also different. MLE's results seem higher than those of the first model and lower than of the second model (because the KH-1995 model has an upward biased problem). Since MLE has better efficiency estimation results among the three models this shows that productive labor hour use was 50.40 percent inefficient compared to the minimum required labor hours.

In all the three models (FE, KH-1995, and MLE) the mean efficiency score of each airport shows that efficiency conditions varied across airports and within the model.

Despite minor estimation differences, the relatively better performing airports were mostly domestic airports with their given output and input levels when compared to other airports. On the other hand, international airports were least performing in terms of labor use technical efficiency levels which implies that they need to take lessons in the deployment of resources and should look at ways of reducing their costs. The relatively low levels of economic activities at some domestic airports and their surrounding region is a result of a limited number of annual passengers being transported. Hence, the time-invariant persistent technical efficiency scores between 90 percent and 100 percent do not necessarily mean that there is no further space for efficiency improvements and instead airports can grow with an overall growth of the economy which ultimately will create an additional air transport demand and will further have space for efficiency of productive labor hour input requirements based on passenger demand and capacity at the airports.

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Chapter Five – Paper 4

Growth Determinants of Ethiopian Air Transport

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Abstract

This study investigates the short-run and long-run growth determinants of Ethiopian air transport using annual time series data for the period 1988-2018. The air transport model is estimated using the autoregressive distributed lag (ARDL) and vector error correction (VEC) models. The study's aim is explaining determinant variations in annual passenger air traffic of Ethiopian Airlines, other airlines, and air freight cargo. The determinants of air transport growth include Ethiopian's average airfare per passenger, national per capita income, real gross domestic product, average exchange rate, the world consumer price index, crude oil prices, and the volume of imports and exports. The national per capita income has a positive and significant short-run and long-run causal relationship with other airlines' passenger growth. However, per capita income only has a long-run positive and significant effect on Ethiopian's passenger growth. The model shows that a large share of the disequilibrium from the previous year's shock converges back to the long-run equilibrium in the current year. Such a highly significant VEC provides evidence of the existence of a stable long-run relationship between the air transport demand and respective explanatory variables. The study's major findings show that most variables are significant in the short-run and in long-run and their respective VEC is also significant and as expected. Macroeconomic variables such as a continued increase in the average exchange rate, crude oil prices, the consumer price index, heavy dependency on imported goods and services, no close substitute for passenger air transport, and growing aggregate demand for Ethiopian air transport result in unexpected signs for some variables. Finally, Ethiopian should consider in its vision the continued changes in the determinant macroeconomic variables to reduce unintended effects.

Keywords: air transport; economic growth; airline performance; passenger and cargo; times series ARDL; VEC model; Ethiopia;

JEL Classification Codes: L93; O4; L25; L91; C22

1. Introduction

1.1 Background of the Study

Transportation services plays an essential role in a country's economy by transporting passengers and goods. The development of the airline industry has broad-based and complex relationships with the world economy, social interaction, and the overall globalization process. Production and consumption of economic activities is highly dependent on transportation. Therefore, air transport is one of the most essential means that provides fast worldwide transport networks enhancing global businesses and tourism. Planning and executing decisions for the air transport industry influence not only the current but also the future development of the industry. This includes airport development plans, flight networking and market shares, investment decisions, and labor hiring (Baikgaki and Daw, 2013; Heshmati and Kim, 2016; Mehmood and Shahid, 2014).

According to Ishutkina and Hansman (2011) unlike other modes of transport, the impact of air transport on economic activities is unique and distinctive and is mainly characterized by its speed, reasonable costs, flexibility, reliability, and safety. The aviation industry owns the only feasible worldwide long-distance transportation mode for high-value perishable commodities and time-sensitive people and is the sole means of access to geographically isolated areas. However, in the presence of high speed railway and cargo shipments, air transport provides little advantage over surface transport for short distance travel and long distance heavy load shipments of goods.

The International Air Transport Association's (IATA) statistical report 2019 points out that of the total revenue ton-kilometers (RTKs), 35 percent of the world traffic measured was in the Asia-Pacific region followed by Europe and North America with 26 percent and 22 percent share respectively. Airlines in the Middle East managed 10 percent of the world traffic. The Latin American and Caribbean region accounted for 5 percent, while African airlines had the remaining 2 percent world traffic. Air traffic has greater growth percentages than most other industries and has doubled in size every 15 years (IATA, 2019). Though the aviation industry is long-lasting and of vital importance for global development, the expansion of the industry is currently encountering challenges and threats throughout the world (ICAO, 2019; ATAG, 2019).

Recent findings of the Airport Council International (ACI, 2019) show that in 2018, global air passenger numbers continued to rise, exceeding 8.8 billion journeys. In thier traffic forecast, emerging and developing economies will account for 60 percent of the passengers. US, China, India, and United Arab Emirates are predicted to lead in air cargo volumes and aircraft movements by 2040 (ACI, 2019). IATA's report identified the main determinant factors for the growth of passenger traffic as a steady decrease in the real cost of air travel – 70 percent in the last 40 years. Such a significant decrease in costs has led to an increase in accessibility of air travel throughout the world (IATA, 2019). The rationale for the soaring growth in air transport according to ACI (2019) is growing economies, declining costs of air travel, more middle class people in developing countries flying, and population growth which are potentially boosting the demand for air transport services globally.

The impact of air transport in Africa in terms of trade, development, and productivity within and across the wider economy and in employment, tourism, and regional integration has a crucial role in African economic development (AFDB, 2019; Goldstein, 2001). Accordingly, in areas which have access to air transport, the aviation industry is acting as a tool in reducing the cost of trade, facilitating the movement of goods and people, and attracting new investments. As shown by AFDB (2019) and IATA (2011), African air transport supports the economy's GDP and has helped to reach US$1.3 billion and generates 155,000 new jobs on the continent. Expansion of air transport has contributed to regional airlines' growth and also enhanced connectivity within Africa. If airfares are affordable, demand for air transport can increase, attracting regional economic cooperation and integration (AFDB, 2019; Goldstein, 2001; IATA, 2011).

Even though air transport in Africa has been playing a vital role in transporting passengers and air freight cargo, coverage and accessibility of air transport services is highly limited. Performance of the African aviation industry is poorer than the rest of the world and it continues facing numerous challenges and obstacles. Africa focused literature (Abate, 2016; and Baroux, 2016; Meichsner et al., 2018; Lubbe and Shornikova, 2017) highlights that African air transport infrastructure is inadequate and still in its early stages of development, has limited coverage, low quality, and the absence of competitiveness. Restricted regulatory arrangements in providing services is the main barrier that continues to obstruct service expansion and quality improvements among African countries. Besides airlines' ability to access foreign markets remains hindered by restrictive regulatory policies. Similarly, African air transport has been lagging in development for decades due to regulatory restrictions and governments' protectionist policies (Meichsner et al., 2018). Besides, many African countries either under or mis-utilize the air transport sector (Bofinger, 2008). Hence, the global challenges of the aviation industry become worse in African aviation's development.

In terms of aircraft capacity and age, African carriers were categorized among the oldest in the world; 80 percent of the aircraft had an age of 10 years or older. This is associated with higher costs for their maintenance, increased fuel consumption, poor reliability, and increased downtime. In terms of utilization, an aircraft in Africa operates 6.9 hours per day while in Europe it operates 9.9 hours per day. This is also due to poor scheduling, night flying restrictions, extended downtime of aging aircraft, and shortage of flight and maintenance personnel (Heinz and O'Connell, 2013; Lubbe and Shornikova, 2017).

On the other hand, the potential of African air transport can be observed from the annual passenger growth rates where Africa has a higher traffic growth rate compared to the global average and this is expected to continue (Lubbe and Shornikova, 2017). To fulfil minimum demand, African air transport requires government policy directions, good governance, and at least start-up capital. Minimum airport infrastructure, mainly investment costs of airports are less than road and railway investment costs. According to Baroux (2016) a 1600-meter runway is long enough as a requirement for short and medium haul aircraft. Air transport has its own international standards and regulations. Lubbe and Shornikova (2017) explain that due to limited implementation of the Africa Union Yamoussoukro Decision and other issues, connectivity on intra-African routes is limited. By the end of 2016, only Ethiopia and Kenya had direct connections to more than half the African countries (Lubbe and Shornikova, 2017; Pearce, 2016). Once Africa overcomes its numerous challenges and constraints, growth in air travel will definitely accelerate.

1.2 Rationale for the study

Growth in Ethiopian airlines (henceforth Ethiopian) air traffic has a long-term historical perspective. During the last 74 years the national flag carrier, Ethiopian, has become a leading African airline and has played a critical role in supporting Ethiopia's economic growth and prosperity. In Ethiopia, other modes of transport are in their infancy with low infrastructure capacity. Besides, the country's topography is high terrain which makes the cost of constructing roads and railways extremely high and inconvenient. As an alternative mode of transport, Ethiopian has provided reliable air transport services at affordable rates for long distance international transport and has a relatively better domestic market as compared to the other modes of transport.

Ethiopian is the first of its kind airline in Africa which has a significant market share with efficient connectivity and significant profitability. Ethiopian's success in terms of sustainability even in global competition has transmitted through the worldwide media[6]. Meichsner et al. (2018) point out three key areas in Ethiopian's success from which African air transport can learn lessons: having a large intra-Africa network, a strong hub with multiple groundswell arrangements for onward connecting traffic, and strategic partnerships with regional African carriers.

The opportunities for air transport's growth have opened the doors for Ethiopian. According to Ethiopian's (2019) annual report, Vision 2025 was completed five years earlier than stipulated. Ethiopian's passenger numbers, aircraft, and revenue are also growing on average up to 15 percent per annum. According to one report, Ethiopian air transport is growing very fast and the momentum will continue in the future with three possible scenarios --- central, high, and low scenarios. The central scenario is 79.5 million passengers (by 2050) with a 5.8 percent growth rate and 25.5 million passengers (by 2030) with a 8.2 percent growth rate (Airport Di Paris Ingineering-ADPI in collaboration with ASCEND Flight Global Consultancy, 2015). A high scenario means 101.6 million passengers (by 2050) with a 6.3 percent growth rate and 30.2 million passengers (by 2030) with a 9.1 percent growth rate. The third scenario is 55.3 million passengers (2050) with a 5 percent growth rate and 20.7 million

6 GCEO of the Ethiopian Ato Tewolde explained to CNN (2016) that the secret behind the success is long-term strategic planning, standard and reliable quality service, and attractive customer handling.

passengers (by 2030) with a 7 percent growth rate. The ultimate purpose of such forecasts is identifying traffic developments and establishing associated capacity requirements for air transport.

Further, among the many contributing factors in the success of Ethiopian, the role that the Government of Ethiopia (Bright and Habte, 2015) plays is large due to the following practical actions. First, the agreement with Trans World Airlines (TWA) to provide technical assistance played a fundamental role in technology and skill transfers and work and management practices to Ethiopian in the last 30 years. Second, the agreement between 44 African countries to deregulate air services and promoting open skies in the African aviation industry. Third, Ethiopian has the privilege of having free market air transport and has relatively free managerial and operational practices. On the other hand, Ethiopia is constrained by limited domestic capital for supporting domestic airlines. Finally, extremely weak exports and limited domestic support have hindered improvements of a global quality (Bright and Habte, 2015).

Nevertheless, the historical development of African airlines started in the post-colonization era with countries trying to own their own international airlines. Though many airlines came up, they did not survive and had to be deregulated. According to Baroux (2016), in Africa 40 countries have at least one airline, while most are suffering from inadequate capital and poor management and are trying to survive without having any development strategies. Political circumstances, inadequate fleet sizes, and poor infrastructure are the main challenges faced by African aviation. As a result, Africa has a very high proportion of very small companies that operate in local markets (Baroux, 2016; InterVISTAS, 2014). Baroux (2016) shows that in Africa about 100 million passengers were transported per year while the actual capacity of 14 African airlines was less than 500,000 passengers per year and only nine airlines were exceeded more than a million people a year. Of all Ethiopian is the leading African airlines who can transported more than 10 million people per year. Overall, the share of Africa airlines is less than 3 percent of global traffic proving that African airlines have limited capacity.

Some crucial factors in the success of the air transport industry (Sivrikaya and Tunc, 2013; Suryani et al., 2010) are proper scientific research forecasting, resource utilization, identifying the level of demand for the services provided, and precise estimations of the factors that determine air transport demand. The determinant factors affecting long term demand for passenger and cargo air travel are demographic and socioeconomic factors (ACI, 2011). The size of the market may be measured by population and GDP while the spending ability can be measured by individual disposable incomes but these too are effected by variations in the exchange rate, the world consumer price index, and world crude oil prices. Suryani et al. (2010) mention that air travel demand is effected by airfares as internal factors, and GDP and population as external factors. Further, Sivrikaya and Tunc (2013) explain that trade between two areas may also be an influencing factor in the demand for air freight and/or transport.

Two important theories are worth mentioning here (Mukkala and Tervo, 2013). The first one is the supply theory of transportation infrastructure and accessibility which argues that airports act as catalysts for local investments while the demand-side theory of economic development determines the need and services of air transport. Though the issue of whether demand-side or supply-side issues dominate is not yet settled. The focus of this study is on the demand side of air transport and specifically explores the main air transport/traffic growth determinant in Ethiopia. In other word, this resreach examines the macro-determinant variables of Ethiopian and other airlines' passengers and international air freight cargo, measure the short-run and long-run relationships and identify their direction of causality effects. This study uses ARDL and VEC modelling for investigating the short-run and long-run causal relationships between air transport growth and the specified macroeconomic variables.

There are limited up to date studies on the Ethiopian air transport industry which focus on the determinant factors of air traffic growth. Growth determinants of Ethiopian air transport are not well documented and the extent of the problem is not yet known, this research will serve as an original reference in African air transport. Based on available data the identified explanatory variables are real GDP, per capita income, the world consumer price index, average exchange rate, world crude oil prices, imports and exports of goods and services, and average prices for Ethiopian. Other control variables such as population, tourism, and industrial output are excluded from the study due to their insignificance and multi-collinearity effects. This study is the first of its kind on Ethiopian air transport. The findings of the macroeconomic determinants briefly show about their impact and whether they have unidirectional or bi-directional causality effects can be used as policy inputs for the air transport sector.

The rest of this chapter is organized as follows. The following section covers theoretical and empirical literature. It describes the main issues and current developments in the air transport industry and summarizes the most important findings and determinants of air passenger and freight growth. Section 3 discusses the model and estimation procedures while Section 4 focuses on the model's specification and estimation. Section 5 discusses the results of the econometric analysis. Finally, Section 6 summarizes the study's findings, provides a conclusion and makes some recommendations based on the study's findings.

2. Literature Review

2.1 Theoretical literature

Air transport has become increasing vital with an increase in globalization for inter-regional and inter-country business expansion and tourism development. The air transport model is basically framed by an interaction between air transportation and economic growth. In other words, this interaction can be shown by the infrastructure and airlines' capabilities. In air transportation, accessibility of airports and airlines to other associated facilities is categorized as supply-side factors while the trend and intensity of air passenger and cargo freight are directly related and effected by the level of economic development (Ishutkina and Hansman, 2011; Mukkala and Tervo, 2012).

Broadly, air transport can be effected and stimulated by micro and macroeconomic aspects. These can be categorized as supply and demand sides of air transport. The supply side aspects are related to internal capacities and firm level regulatory practices, infrastructural facilities and capabilities, and airline specific strategies. On the other hand, the air transportation system is also influenced by aggregate demand and exogenous factors that directly affect the air transport system's development. These are mainly a part of the macroeconomic conditions which are related to demand shocks, recession, political and economic sanctions, and development of alternative modes of transport. Air transport can also help the economy by providing employment and creating enabling access to markets, people, capital, ideas and knowledge, labor supply, skills, opportunities, and resources. Moreover, in the bi-directional causal relationship between the economy and air transport the economy provides capital and generates demand for passenger and freight travel. Similarly, the economy's travel and freight demands are determined by the relative business and leisure attractiveness of goods and services for individual customer (Heshmati and Kim, 2016; Ishutkina and Hansman, 2011). On the other hand, transport demand (Litman, 2019) is the frequency and type of travel most people prefer in specific situations. The most influencing factors in transport demand are prices and service quality. On top of that, demographic, geographic, and economic factors are some additional factors which can affect travel demand among passengers as well as for freight cargo (Litman, 2019).

In addition to competition within the industry, transport demand is also influenced by other global industries. This is usually reflected though major costs for airlines such as jet fuel, labor, and operating costs. They are crucial factors that make airlines more vulnerable to any external shocks and influence their financial and operational performance. As indicated by IATA (2014) and Heshmati and Kim (2016) among the airlines' cost categories only jet fuel accounts for about 25-35 percent of airlines' total operating costs. This implies that political, social, or economic instability in the oil-producing nations can lead to oil prices increasing which will influence the profitability of the industry (Heshmati and Kim, 2016; IATA Annual Review, 2014).

Recent research findings show that the causal relationship between prices and air transport demand varies due to various circumstances. Wadud (2014) found that demand for air transport had an imperfectly reversible relationship with respect to jet fuel prices. Wadud (2015) supports his results using evidence to show that air transport demand did not have a perfect reversible connection with income and jet fuel prices. His study uses time series data to check if airfares and fuel prices had asymmetries in the supply side using a model that captured the potential imperfectly reversible nexus. He found that air transport demand was asymmetric with airfares. Similarly, jet fuel prices passed through to airfares quickly but the response in the opposite direction was slower (Wadud, 2014, 2015).

Wadud (2014) investigated whether air transport was perfectly reversible or not and found that air transport was imperfectly reversible on the effect of income, fuel prices, and airfares on revenue passenger enplanement in the US. Wadud also found the presence of asymmetry and hysteresis effects of income and fuel prices on air transport demand. Despite the degree of elasticity, airfares had a asymmetric effect on aviation demand though the airfares' hysteresis effect was inconclusive. As an extension, Wadud (2015) also investigated the reversibility or imperfect reversibility and found that elasticities of air transport demand with respect to airfares were higher than with respect to fuel prices. An increase in airfares more than fuel prices was found an example of hysteresis effect in cost pass-through concept while falling fuel prices had no effect on airfare was also found that the evidence to the asymmetry cost pass-through.

Kincaid and Trethaway (2007) reviewed airfare elasticities for the last 25 years and came to the following conclusions: (1) sensitivity to airfare changes implies any policy action that increases fares be it taxes or increased landing fees will result in a decline in demand, though the actual demand will also depend on a number of factors; (2) business travelers are less sensitive to fare changes than leisure travelers; (3) fare elasticities on short-haul routes are generally higher than on long-haul routes due to switching to rail or road transport in response to airfare increases; (4) individual air carrier's elasticities are higher than market elasticities; and (5) air travel increases as incomes increase. Kincaid and Trethaway (2007) concluded that the effect of price change in the airline market depended on the circumstances of the applicability of situation.

The basic implications of airfare elasticities are summarized by Kincaid and Trethaway (2007) in three pointes. When an airline increases airfares on a given route it is likely to result in a more than proportionate decrease in air travel and reducing airfares will encourage traffic and increase revenues. This implies that airline specific changes are price elastic. When airfares increase due to airport fees passed on to consumers, the decrease in traffic volumes is less elastic. Lastly, an increase in airfares by all airlines on a wide set of routes may decrease passenger traffic much less than a proportional increase in airfares (Kincaid and Trethaway, 2007).

Adeyemi et al. (2010) studied the importance of modelling asymmetric price responses with the underlying energy demand trend or energy saving technical changes to find out whether they substituted or complemented each other using data from 17 OECD countries for the period 1960-2006. Though most countries preferred energy demand trends to asymmetric price responses, in some countries the two complemented each other while in some other countries they substituted each other. The authors concluded that in energy demand modelling one model was not superior to the other.

Economic development along with national or regional growth in the population are the main incentives for air travel demand increasing. As explained by Mukkala and Tervo (2013), accessibility to air transport is one of several prerequisites for a region’s increased growth and competitiveness. Air traffic provides a timely and reliable mechanism for transferring individuals, goods, and services from one place to another in a globalized world. Fare and quality airline services matter for firms as these support their international competitiveness and are a crucial part of a well-functioning transportation infrastructure. In peripheral areas, the competitive and locational advantages may be strongly influenced by airlines’ networks. Easy accessibility attracts firms and economic activities to a region and stimulates employment growth.

There are various complex factors that affect air traffic growth throughout the world. The complexity issues are expressed in circumstances where some part of air travel is growing significantly while some other parts are stagnant or floundering. Vasigh et al. (2008) summarize the main factors as:

- The level of prosperity in a region measured by GDP. Increased prosperity leads to increased demand for air travel and increased economic activities help generate employment, which ultimately leads to an increase in business travel. This shows business travel is the primary reason while increased economic activities also spur growth in air cargo. The amount of leisure time can also affect demand for vacation flights.
- The experience of the deregulation in the 1970s showed a decrease in the real cost of air travel and also created growth in air traffic. As airfares declined, a larger number of people could afford air travel and they took advantage of this. So, low-cost carriers generated increased air travel with low fares and airports experienced tremendous growth in passenger numbers. Another factor in air traffic’s growth is population growth accompanied by income growth.
- Economic liberalization that lifted price control and excessive regulations enabled more air travel. Moreover, the freedom for airlines to fly to whatever destinations

they wanted made flying more convenient for passengers as they had more non-stop flights at a greater frequency. Political instability and terrorist attacks can also affect air travel.

- Among the many factors, economic impact is the most important in demand for air transport. The economic impact of air transport can be divided into direct, indirect, and induced impacts. Direct impacts represent economic activities such as employment and resource demand and utilization. Indirect economic benefits include financial benefits that are attributed to airport/airline activities including hotels, restaurants, and other retail activities. Finally, induced economic impacts are multiplier effects of direct and indirect impacts.

Baltaci et al. (2015) and Debbage (1999) state that investments in passenger air transport can effect a regional economy in two different ways. First, airports will contribute additional income to the local regional economy by making new and direct investments for creating employment opportunities. Moreover, indirect and induced spending related to constant capital investments on a large scale will create benefits for the local economy's development by creating various investment and employment opportunities. Secondly, airlines' networks can change a region's economic connections with other regions and countries.

Ishutkina and Hansman (2011) focused on both worldwide and country-level analyses to describe the relationship between air transportation and economic activities. They discuss how economic, infrastructural, institutional, and geographic factors affect the mapping of cargo and passenger flows to enable flows of labor, knowledge, investments, remittances, tourism, and goods. They found that air transportation services and economic development were interdependent and interacted through a series of feedback relationships. Their aggregate trend analysis showed that there was a correlation between air travel and GDP. However, growth rates and the mechanisms behind the interaction differed for individual economies.

2.2 Empirical literature

Airline freight transport is an important mode of transport that helps integrate marketplaces by removing the barriers between economies and shortens the distances in a most efficient way from a time perspective. Economic activities shape investments, trade, and transportation through logistical channels which is also an inevitable result of accelerated globalization and this naturally effects the development of a country (Artar et al., 2016).

Empirical literature clearly shows that there is a typically strong correlation between air traffic and economic growth. Mukkala and Tervo (2012) state that the causation between the two is not clear. They did an empirical analysis based on European level annual data from 86 regions and 13 countries on air traffic and regional economic performance for the period 1991-2010. Their results suggest that the causality processes were homogenous from regional economic growth to air transport growth. There was causality of air traffic for regional growth in the peripheral regions, but the causality was less evident in core regions. Their findings also show that air transportation played a crucial role in boosting development in remote regions.

Mehmood and Shahid (2014) empirically examined the aviation-led growth hypothesis for the Czech Republic by testing causality between aviation and economic growth. They used econometric tests such as unit root tests, test of co-integration purposed by Johansen (1988), and other techniques for estimating the co-integration equation for a time span of 42 years from 1970 to 2012. Their empirical results implied that aviation and economic growth were co-integrated in the long-run and the relationship held in the short-run as well.

Mehmood and Shahid (2014) argue that empirical work on aviation-led economic growth is very new and is still developing. Wadud (2014) analyzed simultaneous modelling using a seemingly unrelated regression (SUR) framework to jointly model passenger and cargo demand at the Shahjalal International Airport in Dhaka, Bangladesh. Assuming that there was a correlation among air passenger and air cargo demand models, Wadud found that the SUR approach was a more efficient and reliable estimate than OLS and individual co-integration methods. Passenger and cargo demand at the airport are forecast up to 2030.

Mehmood and Shahid (2014) also examined the relationship between aviation and economic growth by applying the Johansen co-integration approach for the long-run, and the standard error correction method for the short-run. They empirically tested the relationship between aviation demand and GDP for Brazil. They used passenger-kilometer as a proxy for aviation demand and found a long-run equilibrium between the two variables using the bivariate vector autoregressive model. Their findings reveal strong positive causality of GDP on aviation demand but relatively weaker causality the other way around.

Mehmood et al. (2014) studied the co-integration, reaction to shocks, and causality relationships between demand for aviation and economic growth in Bangladesh. Their results showed that aviation and economic growth were co-integrated in the long-run and the relationship held in the short-run as well. The number of passengers (lnPAX) reacted positively and strongly to a shock in GDP. The maximum impact occurred after two years (t+2) while lnGDP showed a small and quick negative reaction in the first period but a positive and sustained effect in the coming years. This positive relationship can be attributed to direct and indirect effects of aviation. This gives further impetus to economic activities and hence growth.

In India, Basak et al. (2013) examined the growth in air cargo for studying the relationship between air cargo and major factors influencing its growth. The determinant variables were air freight, GDP, foreign trade, and jet fuel prices. The growth potential of the Indian air cargo industry was analyzed using a multiple regression analysis which showed that GDP and trade had a positive impact on the growth of air cargo while fuel prices had a significant and negative impact.

Mehmood et al. (2013) investigated the relationship between Romanian aviation and its economic growth. They applied the cointegration equation for the period 1970 to 2012. Their results showed the existence of co-integration between aviation demand and economic growth both in the long-run and in the short-run. Graphic methods such as an impulse response function and variance decomposition were also used. Aviation demand made a positive contribution to economic growth. Their findings will help in chalking out the importance of the aviation industry in Romania's economic growth. The authors further particularized that this positive relationship can have a direct and indirect impact of aviation. Baltaci et al. (2015) state that airline transport is considered a very effective factor in explaining countries' economic growth. They found that Turkish air transport was positively effecting the region's economic growth.

Abate (2016) examined the economic effects of air transport liberalization in Africa by studying city pair routes to/from Addis Ababa. He estimated passenger demand, fares, and departure frequency models for analyzing the causal effects of liberalization policies on reducing fares and improving service quality, as would be expected under liberalization. Abate's (2013) findings show an up to 40 percent increase in departure frequencies on routes that experienced liberalization compared to those governed by restrictive regimes.

Due to the globalization process (Artar et al., 2016), passenger and freight transportation demand has increased tremendously. Transporting air freight has a natural impact on the distance that the freight is carried over. International logistics provide economic utilities in a sustainable manner for global competition. Supply and distribution channels are highly sophisticated, powering the economy and boosting their share in GDP. Many countries are effected by growing liberalization of the air transport market. Artar et al., (2016) analyzed the relationship between GDP and air freight traffic in Turkey and found that a statistically significant relationship existed between the two. The fact that the aviation industry should get policy attention to play its role further in determining economic growth was thus stressed by the authors. They mwntioned that formal incentives should be given to the aviation industry to increase its macroeconomic contributions.

3. Model Specification and Estimation Techniques

3.1 Econometric modelling of air transport demand

Econometric models are designed for examining the relationship between various economic forces and economic outcomes such as demand for goods or services. Many empirical studies use a wide range of explanatory factors in modelling air travel demand including GDP, income, airfares, exchange rates, travel time, population, export and import values, aircraft movements, frequency of flights, and other variables which directly affect air travel demand. Among these, GDP which represents the size of the economy is one of the most important variables in many studies.

Demand for public transport, road freight facilities, or airline services have a derived demand for other functions related to the demand levels for products or services

(Adekunle, 2010). In addition to the standard econometric demand analysis, Airport Council International (ACI, 2011) used econometrics to forecast growth in air travel demand since the early 1970s. The model was developed by the British Air Transport Authority (BAA) as a series of models to predict growth of a range of European airports as part of a study commissioned by the Western European Airports Association.

For applying an econometric forecasting approach, Airport Council International (ACI, 2011) recommended beginning by examining historic traffic and survey data for breaking down the total number of passengers by routes and types of passengers. By comparing the growth patterns of each element against relevant economic measures such as GDP, trade, and personal consumption, it is possible to establish which are the most important economic drivers and the sensitivity of traffic demand to the pressures of these drivers. According to ACI, this process is expected to highlight the impact of any external events on growth patterns and show whether any effects were still being felt at the time the forecast was done.

The concept of elasticity can be applied for explaining the degree to which a change in one of the determinant variables, everything else being equal, will stimulate change in an air traffic segment. In effect, this is stimulating the model which converts the energy of the economic driver into the speed of traffic growth forecast by ACI (2011). Airfares, cost per km, or price of jet fuel represent deterrence in flying and generally have negative effects if included in the demand model. Wadud (2014) asserts that price elasticities have always been an important parameter for researchers and policymakers and there are a significant number of studies that estimate this parameter. Price elasticities can also vary depending on the trips' purpose with business travel being less elastic (ACI, 2011; Wadud, 2014).

Bearing the variable description in mind, an empirical model for the growth determinants of Ethiopian air transport using the ARDL approach, the SUR regression for this study is assumed as an aggregate and can be specified separately in three models as:

Equation 1: Ethiopian's passenger growth determinants:

(4.1) $\ln\mathrm{Ye} = f(\ln\mathrm{ETAP}_t, \ln\mathrm{AXCR}_t, \ln\mathrm{CROILPB}_t, \ln\mathrm{PCIM}_t)$

Equation 2: Other airlines' growth determinants:

$$(4.2)\quad \ln Yo = f(\ln WCPI_t, \ln AXCR_t, \ln CROILPB_t, \ln PCIM_t)$$

Equation 3: Ethiopian air freight cargo's growth determinants:

$$(4.3)\quad \ln Yc = f(\ln RGDP_t, \ln WCPI, \ln AXCR, \ln CROILPB, \ln XEM)$$

where lnYe is the logarithm of Ethiopian's passengers from and to Addis Ababa Bole International Airport at time period t, which is the dependent variable for the first equation; lnETAP is the logarithm of average price per passenger for Ethiopian which has an inverse relationship with Ethiopian's passengers. lnPCIM is the logarithm of national real per capita income in Thousand-Birr which is expected to have a positive and significant effect; CROILPB is the logarithm of crude oil prices at time period t with a negative impact on the dependent variables; lnAXCR is the logarithm of average exchange rate with an expected opposite sign as the dependent variable.

The second equation specified as lnYo, that is, log of other airlines' passengers whose destination and departure is Addis Ababa. While Yc is log of Ethiopian's air freight cargo from and to Addis Ababa Bole International Airport in metric tons is the third equation used in this study. Other variables such as lnRGDP is the log of real gross domestic product, lnWCPI is log of the world consumer price index, and lnXEM is the log of total imports and exports of goods and services which is expected to have a positive impact on the dependent variables measured in 2011 constant prices.

As is evident from this analysis, economic growth holds valuable information for forecasting aviation demand. This positive relationship can be attributed to direct and indirect effects of aviation. Direct effects include transportation of labor and goods. Indirect benefits include benefits that accrue to other industries through backward and forward linkages with the aviation industry. This study is a pioneer in research in the field of aviation using sophisticated tools. The scope of this research on aviation can be extended by using a cross-country analysis.

3.2 The Data

The data used in this study comes from multiple sources. The data covers the period 1988-2018. Per capita income (PCIM), the world consumer price index (WPCI), and crude oil prices (Oil) are collected from different national account series of MoF which were also linked for harmonization with NBE. Air passenger traffic (Ye) and freight cargo (Yo) data comes from Ethiopian air freight cargo, airports, and the Ethiopian Airlines Group’s annual reports. Data on real GDP is obtained from MoF by deflating the nominal GDP by the GDP deflator (base year 2011). Population data is obtained from various issues of NBE. Per capita income is calculated by dividing real GDP by the population.

Table 4.1 gives the important macroeconomic variables such as the world consumer price index, crude oil prices, imports and exports of goods and services, number of tourists, domestic industrial output, air freight cargo, Ethiopian and other airlines’ passengers transported through Addis Ababa International Airport. The table contain summary statistics for each variable.

Table 4.1: Descriptive statistics of Ethiopian air transport’s growth determinant variables (1988-2018, 31 observations)

Variables	Description of variables	Mean	Median	Maximum	Minimum	Std. Dev.
Ye	Ethiopian’s passengers at Addis Ababa (number)	2152700	875336	9225735	319780	2377658
Yc	Ethiopian’s freight cargo at Addis Ababa (Kg ‘000’)	78185.078	36508.444	243,000	20895.410	69404.965
Yo	Other airlines’ passengers at Addis Ababa (N)	527447	228158	1741242	59487	4963081
RGDP	Real gross domestic product (million Birr)	351000	228000	932000	130000	247000
PCIM	Per capita income ETB	4732.74	1171.21	23061.49	428.38	6377.74
ETAP	Ethiopian’s average price per passenger ETB	3622.04	2499.12	8351.46	694.55	2563.65
WCPI	World consumer price index	118.74	112.79	192.74	67.23	35.75
AXCR	Average USD to ETB exchange rate	10.18	8.58	27.00	2.07	6.74
CROILPB	Crude oil prices converted into ETB	11562.08	2672.64	55362.11	78.72	16161.23
XEM	Volume of total imports and exports of goods and services (million ETB)	133000	88000	345000	23400	106000
Tourists (numbers)		307093	156327	933343	76450	273156
Domestic industrial output (million ETB)		204	190	293	152	35.56
Number of observation		31	31	31	31	31

Source: Author's calculations based on data from the Ethiopian Airlines Group and EAE, MoF, and NBE (1988-2018).

The average real per capita income in the specified period was 4732.74 Birr with a maximum of 23061.49 and minimum of 428.38 Birr per person. The average real gross domestic product was 351,000 million ETB and average import and export volume was 133,000 million ETB. Similarly, total domestic industrial output value on average was 204 million ETB. This means the ratio of imports and exports to real gross domestic product was approximately 1:3 while the ratio of industrial output to imports and exports was 0.0015:1 which is extremely low. This shows that the Ethiopian economy is highly import dependent as compared to domestic industrial output. Such extreme dependency on external products may have an estimation effect on the macroeconomic variables. Imports and exports of goods and services will have a direct effect on the world consumer index, crude oil prices, and exchange rate. The variables tourist volumes, industrial output, and population were excluded from the model's specifications due to a problem of serial correlation.

3.3 Estimation Methods

3.3.1 Non-stationary processes and testing

It is common for most key economic variables such as GDP, consumption, and the real price level to have strong increasing trends. With a given lag for each series, the stationarity series strongly influences the variables' behavior and properties. In the stationarity process, the variables have constant mean reversion in the long-run and constant variance over time. Any shock to the stationary series is temporary and it gradually dies away. This means that it will revert to its long-run mean and long-term forecast of stationarity will be converged to the unconditional mean of the series. Hence, a covariance stationary series exhibits mean reversion and fluctuations around the constant long-run mean and has a finite time-invariant variance which diminishes as the lag length increases. In other words, a stationary series has a constant mean, constant variance, and constant autocovariances (Brooks, 2014; Enders, 2015; Greene, 2018).

On the other hand, a non-stationary series has a permanent effect so that the mean and variance of a non-stationary time series are time varying. This means that the mean does not return over time in the long-run, variance is time varyingly increasing to infinity. A non-stationary series produces spurious regressions; its t-ratio of the coefficient is not significantly different from zero, that is, the t-ratio will not follow t-distribution, F-statistics and F-distribution, additionally R2 will be extremely low (Brooks, 2014; Enders, 2015; Greene, 2018).

Hence, a non-stationary series needs a transformation or differencing for obtaining stationary data and for minimizing the behavior of the trending variables. Greene (2018) and Enders (2015) explain that a linear stochastic equation has three distinct components --- trend, seasonal, and irregular conditions: $y_t = trend + seasonal + irregular$.

A non-stationary time series can be characterized by two models – the random walk model with a drift:

(4.4) $y_t = \mu + y_{t-1} + u_t$

where u_t is a white noise disturbance term. If there is a stationary trend in the data, we call it stochastic non-stationary or unit root process where the root of the characteristic equation (1-z) = 0. Hence, stationarity can be induced by differencing d times before it become stationary. This is known as integrated of order d $y_t \neg I(d)$ if $y_t \neg I(d)$ then $\Delta^d y_t \neg I(0)$. A process with no unit root I(0) is stationary and I(1) is stationary after the first difference. If there are two unit roots it can be differenced two or more times, that is, I(2). The study's methodology depends on the order of integration. An ARDL model fits with no unit root I(0) and I(1) and the trend which is a stationary process:

(4.5) $y_t = \alpha + \beta t + u_t$

In both the cases u_t is a white noise disturbance term. This is known as deterministic non-stationarity and de-trending is required to make it stationary. Running a regression gives the trend stationarity and conducting a subsequent estimation of the residual helps remove the linear trend.

A. Dickey-Fuller tests

Consider the autoregressive lag model $y_t = \alpha_1 y_{t-1} + \varepsilon_t$, if we subtract y_{t-1} from both the sides, we get:

(4.6) $\Delta y_t = \gamma y_{t-1} + \varepsilon_t$

(4.7) $H_0 : \gamma = 0$ is tested against $H_1 : \gamma \prec 0$

If H_0 is rejected, then γ_t does not contain a unit root. If H_0 is not rejected then γ_t contains a unit root.

To determine whether $\alpha_1 = 1$ implies that $\gamma = \alpha_1 - 1$. Hence, testing $\alpha_1 = 1$ is almost the same as testing the hypothesis $\gamma = 0$. For testing the presence of the unit root, Dickey and Fuller (1979) considered the following three equations:

(4.8) $\Delta y_t = \gamma y_{t-1} + \varepsilon_t$

(4.9) $\Delta y_t = \alpha_0 + \gamma y_{t-1} + \varepsilon_t$

(4.10) $\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 t + \varepsilon_t$

where the three regressions indicate the presence of the elements deterministic α_0 and $\alpha_2 t$. Equation 4.8 is a pure random walk model, Equation 4.9 added an intercept term or drift term, and Equation 4.10 includes both a drift and linear time trend.

Dickey and Fuller (1981) also introduced three additional F-statistics (ϕ_1, ϕ_2 and ϕ_3) to test the joint hypothesis of the coefficients. These are null hypothesis $\gamma = \alpha_0 = 0$ using ϕ_1 for (3.10), the hypothesis including the time trend can also be estimated using a joint hypothesis $\alpha_0 = \gamma = \alpha_2 = 0$ is tested using ϕ_2 statistics while the last joint hypothesis $\gamma = \alpha_2 = 0$ is tested with ϕ_3. The test will be valid if ε_t is white noise and is not assumed to be autocorrelated. Otherwise the test will be oversized and the true size will be higher than the nominal size (Brooks, 2014). Hence, the solution is 'augmenting' the test using p lags of the dependent variable.

As Enders (2015) calculated the covariance of y_t and y_{t-s}, that is, $\gamma_{t-s} = (t-s)\sigma^2$, the correlation coefficient ρ_s can be obtained by dividing γ_{t-s} by the product of the standard deviation of y_t multiplied by the standard deviation of y_{t-s}. As the estimated value of α_1 is directly related to the value of ρ_1, then α_1 is biased and less than the true value of unity. Hence, according to Enders (2015) the usual t-test cannot be used to test the hypothesis of $\alpha_1 = 1$.

B. The augmented Dickey-Fuller Test

The DF test described earlier assumed that the disturbance in the model was white noise. We can obtain the general form of the Augmented Dickey-Fuller (1981) test written as (Dickey and Fuller, 1979):

$$(4.11)\quad \Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t$$

$$(4.12)\quad \gamma = -(1 - \sum_{i=1}^{p} \alpha_i) \quad \text{and} \quad \beta_i = \sum_{i=1}^{p} \alpha_i$$

where the lags of Δy_t represent any dynamic structure in the dependent variables that ensures ε_t is not autocorrelated (Brooks, 2014). The coefficient of interest and testing procedure is the same as in the Dickey-Fuller test illustrated earlier but the test is conducted on γ with the same critical values from DF.

The Augmented Dickey-Fuller tests the null hypothesis of unit root $(\alpha = 1)$ against the alternative hypothesis of $\alpha < 1$ is written as:

$$(4.13)\quad y_t = \delta_0 + \delta_t t + \alpha y_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta y_{t-1} + \varepsilon_{1t}$$

where Δ is a first difference operator and n is the lag length in the model. The lag length is determined based on the Akaike information criterion (AIC).

Taking Equation 4.11 the random walk form can be obtained by imposing $\mu = 0$ and $\beta = 0$. Then in both the parameters the trend stationary model is left free. The test statistic of ADF follows the original DF tests (Brooks, 2014; Enders, 2015; and Greene, 2018). Accordingly, the two test statistics are:

(4.14) $DF_{\tau} = \dfrac{\hat{\gamma}-1}{Est.Std.Error(\hat{\gamma})}$ and $DF_{\tau} = \dfrac{T(\hat{\gamma}-1)}{1-\hat{\gamma}_1-...-\hat{\gamma}_p}$

This is a general formulation that can accommodate higher order autoregressive processes in ε_t (Greene, 2018).

C. Phillips-Perron tests

In relation to the distribution of the error term, Phillips and Perron (1988) developed a test based on a generalization of the Dickey-Fuller procedure to allow some fairly mild assumptions (Enders, 2008). ADF test is biased towards accepting the null hypothesis of the unit root in the series if the series exhibits a significant structural break. This implies that in the presence of structural breaks, the Phillips-Perron test (Phillips and Perron, 1988) gives more robust estimates. Enders (2015) explains the Phillips-Perron test specified as:

(4.15) $y_t = \alpha_0^* + \alpha_1^* y_{t-1} + \mu_t$

and

(4.16) $y_t = \tilde{\alpha}_0 + \tilde{\alpha}_1(t - T/2) + \tilde{\alpha}_2 y_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta y_{t-1} + \mu_t$

where T is the number of observations and m is the lag length which can be determined based on the suggestion given by Newey and West (1987). The disturbance term μ_t is expected to have a value $E(\mu_t) = 0$. The Phillips-Perron test allows the disturbance term to be weakly dependent and heterogeneously distributed which is less restrictive for the Dickey-Fuller independence and homogeneity assumption. More details of the characteristics of Phillips and Perron's distribution and the derived test statistics about the coefficients α_i^* and $\tilde{\alpha}_i$ to test the data under the null hypothesis are provided in Phillips and Perron (1987).

In this study, annual passengers, freight cargo, GDP, the consumer price index, average airfares, tourists, and world oil prices show an increasing trend.

4. The Empirical ARDL Model's Specification

4.1 General concept of the ARDL framework

There are a number of cointegration techniques in economics literature. Originally the ARDL approach was developed by Pesaran and Shin (1995, 1998) and Pesaran et al. (1996, 1999, 2001). It has become popular in recent years. Unlike traditional cointegration models, the ARDL co-integration model has three advantages. First, ARDL does not require all the variables to have the same order of integration. This means that the variables in the study can be of the order of one, order of zero, and fractional integrated (that is, I(0) or I(1) or mutually integrated). There is a prerequisite that none of the explanatory variables are I(2) or of a higher order, that is, the ARDL procedure will be inefficient in the existence of I(2) or higher order series. Second, the ARDL model is relatively more efficient for small and finite sample data sizes. Finally applying the ARDL technique means a general to specific modelling framework by taking a sufficient number of lags to capture the data generating process. This results in an unbiased long-run estimated model (Belloumi, 2014; Lee, 2012; Pesaran et al., 1999, 2001).

In addition, traditional co-integration methods may also have problems of endogeneity, whereas the ARDL method can distinguish between dependent and exogenous explanatory variables and remove the problems that may arise due to the presence of autocorrelation and endogeneity. The ARDL cointegration estimates short-run and long-run relationships simultaneously and provides unbiased and efficient estimates. The appropriateness of using the ARDL model is that it is based on a single equation framework. The ARDL model requires a sufficient number of lags in the data generating process in a general to specific modelling framework. Unlike other multivariate co-integration techniques such as Johansen and Juselius (1988), the ARDL model allows the co-integration relationship to be estimated by OLS once the lag order of the model is identified. The VEC model can also be drawn by following the ARDL approach. These advantages of the ARDL model over other standard cointegration techniques justifies its application in the context of my study.

According to Pesaran and Shin (1999), Pesaran et al. (2001) and Narayan and Smyth (2006), the ARDL approach requires the following three steps. The first step is the bounds cointegration test. This test's result determines whether there is a long-run relationship between the variables or not. The second and third steps are estimating the long-run and short-run elasticities conditional on the first step. The second step estimates the coefficient of a long-run relationship and determines its value. The third step is estimation of the short-run elasticities of the variables with the error correction that represents the ARDL model. To sum up, if the variables are co-integrated we can specify both short-run (ARDL) and long-run (VEC) elasticities otherwise only the short-run (ARDL) model can be specified. This means the bounds co-integration test confirms the relationship between each variable in the model. By applying ARDL VEC's model version the speed of adjustment to the equilibrium is determined.

In line with the Solow growth model (1957), this study follows the time series ARDL approach for analyzing the growth determinants of Ethiopian air transport. According to several studies (Endres, 2015; Greene, 2018; Kripfganz and Schneider, 2018; Narayan and Smyth, 2006), the general ARDL model is represented as:

$$(4.17)\quad Y_t = \gamma_{0i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \sum_{i=0}^{q} \beta_i X_{t-i} + \varepsilon_t$$

where Y_t' is a vector that implies that the dependent variable is a function of its lagged value and the variables in $(X_t')'$ are also current and lagged values of exogenous variables that are allowed to be purely I(0) or I(1), co-integrating; β and δ are coefficients of the lagged dependent variable and exogenous variables; γ is the intercept; $i = 1,....,k;$ and p, q are optimal lag orders of the dependent and regressors respectively where p, q may not necessarily have the same lag length, ε_t is a vector of the random error term with zero mean constant variance and is serially uncorrelated.

4.2 ARDL model's specification for the growth determinants of Ethiopian air transport

The growth determinants of Ethiopian air transport using the ARDL approach and the seemingly unrelated regression (SUR) equation is assumed to take the form of the following three equations.

- Ethiopian's passenger growth determinants
- Other airlines' passenger growth determinants
- Ethiopian air freight cargo's growth determinants

This study follows the three-step approach described earlier for identifying the determinants of Ethiopian air transport growth. Accordingly, the general bounds test for the three equations can be conducted assuming pairwise Granger causality of each variable as being dependent on its own VEC model equation. Based on Narayan and Smyth (2006) the ARDL bound test co-integration model specification follows.

Ethiopian's passenger growth determinant equations have the same number of variables and can be written in the conditional ARDL (p, q_1, q_2, q_3, q_4) model with five variables specified as follows. In the following, the possible endogenous variables (lnPCIM and lnETAP) that appear in the first equation are also outlined:

(4.18.1)

$$\begin{aligned}\Delta \ln Ye_t = {} & \alpha_{01} + b_{11} \ln Ye_{t-i} + b_{21} \ln PCIM_{t-i} + b_{31} \ln AXCR_{t-i} + b_{41} \ln CROILPB_{t-i} + b_{51} \ln ETAP_{t-i} \\ & + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Ye_{t-i} + \sum_{i=1}^{q} \alpha_{1i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{1i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{1i} \Delta \ln CROILPB_{t-1} \\ & + \sum_{i=1}^{q} \alpha_{1i} \Delta \ln ETAP_{t-1} + \varepsilon_t\end{aligned}$$

$$\begin{aligned}\Delta \ln PCIM_t = {} & \alpha_{02} + b_{12} \ln Ye_{t-1} + b_{22} \ln PCIM_{t-1} + b_{32} \ln AXCR_{t-1} + b_{42} \ln CROILPB_{t-1} + b_{52} \ln ETAP_{t-1} \\ & + \sum_{i-1}^{p} \alpha_{1i} \Delta \ln Ye_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} \\ & + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln ETAP_{t-1} + \varepsilon_t\end{aligned}$$

$$\begin{aligned}\Delta \ln ETAP_t = {} & \alpha_{05} + b_{15} \ln Ye_{t-1} + b_{25} \ln PCIM_{t-1} + b_{32} \ln AXCR_{t-1} + b_{45} \ln CROILPB_{t-1} \\ & + b_{55} \ln ETAP_{t-1} + \sum_{i-1}^{p} \alpha_{1i} \Delta \ln Ye_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} \\ & + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln ETAP_{t-1} + \varepsilon_t\end{aligned}$$

The general bounds test for the second equation assumes that all variables are dependent. Accordingly, other airlines' passenger growth determinant equations can be written in the conditional ARDL (p, q_1, q_2, q_3, q_4) model with five variables specified as:

(4.18.2)

$$
\begin{aligned}
\Delta \ln OAIRLPAX_t = {} & \alpha_{01} + b_{11} \ln OAIRLPAX_{t-i} + b_{21} \ln PCIM_{t-i} + b_{31} \ln AXCR_{t-i} + b_{41} \ln CROILPB_{t-i} \\
& + b_{51} \ln WCPI_{t-i} + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln OAIRLPAX_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} \\
& + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln WCPI_{t-1} + \varepsilon_t
\end{aligned}
$$

$$
\begin{aligned}
\Delta \ln WCPI_t = {} & \alpha_{05} + b_{15} \ln OAIRLPAX_{t-1} + b_{25} \ln PCIM_{t-1} + b_{32} \ln AXCR_{t-1} + b_{45} \ln CROILPB_{t-1} \\
& + b_{55} \ln WCPI_{t-1} + \sum_{i-1}^{p} \alpha_{1i} \Delta \ln OAIRLPAX_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} \\
& + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \varepsilon_t
\end{aligned}
$$

The general bounds test for the third equation of Ethiopian air freight cargo's growth determinants assuming all variables as dependent have a conditional ARDL $(p, q_1, q_2, q_3, q_4, q_5)$ model with six variables specified as:

(4.18.3)

$$
\begin{aligned}
\Delta \ln ETCARGOADD_t = {} & \alpha_{01} + b_{11} \ln ETCARGOADD_{t-i} + b_{21} \ln PCIM_{t-i} + b_{31} \ln AXCR_{t-i} \\
& + b_{41} \ln CROILPB_{t-i} + b_{51} \ln WCPI_{t-i} + b_{61} \ln XEM_{t-i} + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln OAIRLPAX_{t-i} \\
& + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} \\
& + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \sum_{i=1}^{q} \alpha_{6i} \Delta \ln XEM_{t-1} + \varepsilon_t
\end{aligned}
$$

$$
\begin{aligned}
\Delta \ln XEM_t = {} & \alpha_{05} + b_{15} \ln OAIRLPAX_{t-1} + b_{25} \ln PCIM_{t-1} + b_{32} \ln AXCR_{t-1} + b_{45} \ln CROILPB_{t-1} \\
& + b_{55} \ln WCPI_{t-1} + b_{61} \ln XEM_{t-i} + \sum_{i-1}^{p} \alpha_{1i} \Delta \ln OAIRLPAX_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} \\
& + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \sum_{i=1}^{q} \alpha_{6i} \Delta \ln XEM_{t-1} \\
& + \varepsilon_t
\end{aligned}
$$

In all the three equations (b_{yy}, b_{yx}) are long-run multipliers, (α_0) is the drift, Δ is the first difference, and ε_t is the random disturbance term or exogenous components, while the lagged value Δy_t or/and current and lagged values of the independent Δx_t are used for modelling the short-run dynamics. Hence, testing for the absence of a cointegration relationship between y_t and x_t can be done by excluding the lagged level variables y_{t-1} and x_{t-1} (Narayan and Smyth, 2006; Ozkan and Karaman, 2011).

The ARDL model with an order of (p, q_1, q_2, q_3, q_4) represents the first and second equations while $(p, q_1, q_2, q_3, q_4, q_5)$ is the order for the third equation. Similarly, the three dependent variables are lnYe representing the log of Ethiopian's passengers from and to Addis Ababa in number. LnYc is log of Ethiopian's air freight cargo transported in kg and lnYo is other airlines' passenger transport services originating and departing from Addis Ababa International Airport. While the explanatory variables specified by the ARDL model are log of Ethiopian's per capita income (lnPCIM) in Birr, log of Ethiopian's average price per passenger (lnETAP) in Birr, log of the average exchange rate (lnAXCR) USD to ETB, log of crude oil prices in Birr (lnCROILPB), and log of total volume of imports and exports of goods and services in Birr (lnXEM). LnRGDP is log of real gross domestic product in Birr.

A. Bounds test for cointegration

For specifying the cointegration model, the bounds test is done to ensure if all the variables are cointegrated or not. In other words, if we cannot reject the null hypothesis, we can conclude that there is a long-run (VEC) cointegration relationship, otherwise we will specify only the short-run model. As Belloumi (2014) states, the bounds test is basically joining the F-statistics with the asymptotic distribution of a no cointegration null hypothesis assumption. In the ARDL bounds approach the first step is estimating the equations using OLS.

Pesaran et al. (2001) suggested the existence of a long-run relationship is tested using the F-test for the joint significance of the coefficients among the lagged levels of the variables

The hypothesis is: $H_0 : b_{1i} = b_{2i} = b_{3i} = b_{4i} = b_{5i} = 0$ where $i = 1,2,3,4,5$. This implies no cointegration, that is, the coefficients of the long-run equation are all equal to zero.

If we reject the hypothesis of no cointegration then we are in favor of the alternative hypothesis that there is a long-run relationship and we can specify the VEC model.

The alternative hypothesis is: $H_1 : b_{1i} \neq b_{2i} \neq b_{3i} \neq b_{4i} \neq b_{5i} \neq 0$ where there is a cointegration, the coefficient of the long-run equation is not equal to zero. Rejecting the alternative hypothesis implies no cointegration and no long-run relationship.

According to Pesaran et al. (2001) the significance level can be found using two sets of critical values. The first assumption is that all the variables in the ARDL model are integrated of order zero while the second assumption is calculated with an integrated order of one. When the values of the F-statistics exceed the upper critical bounds of no cointegration the null hypothesis is rejected and if the test statistics are lower than the lower bounds values, the null hypothesis of no cointegration is accepted, otherwise the test of cointegration is inconclusive if it is between the upper and lower bounds.

Moreover, structural lags can be established by using minimum Akaike's information criteria (AIC) or the Bayesian information criterion (BIC). Following the AIC/BIC criteria, this study chooses a maximum lag order of 2 for the conditional ARDL and VEC models. The results of the F-statistics are given in Table 4.6 and their values for Equation 4.1 is (14.18), for Equation 4.2 (14.98), and for Equation 4.3 (8.56), that is Ethiopian's passengers, other airlines' passengers, and Ethiopian air freight cargo has F-statistics higher than the upper bounds critical values at the 2.5 level. This shows that the null hypothesis of no cointegration among the variables of each equation is rejected and it is proved that there is a long-run relationship between the variables in all the three equations.

B. The Long-run ARDL model

Following the cointegration test, the conditional ARDL$(p, q_1, q_2, q_3, q_4, q_5)$ long-run model can be estimated based on Equations 4.18.4-4.18.6. This model can also help specify the models for OLS and SUR. Accordingly, the ARDL, OLS, and SUR models for Ethiopian's passengers, other airlines' passengers, and Ethiopian's air freight cargo's growth determinants can be specified and estimated as:

Ethiopian's passenger growth determinants equation:

(4.18.4)

$$\Delta \ln Ye_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Ye_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln ETAP_{t-1} + \varepsilon_{1t}$$

Other airlines' passenger growth determinants equation:

$$\Delta \ln Yo_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Yo_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \varepsilon_{2t} \quad (4.18.5)$$

Ethiopian's air freight cargo growth determinants equation:

$$\Delta \ln Yc_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Yc_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \sum_{i=1}^{q} \alpha_{6i} \Delta \ln XEM_{t-1} + \varepsilon_{3t} \quad (4.18.6)$$

where all variables are as previously defined and the order of ARDL $(p, q_1, q_2, q_3, q_4, q_5)$ is I(2) as selected using AIC.

C. Short-run dynamics and the VEC model

We know from the bounds test that there is a cointegration in the model in each equation. The existence of a long-run relationship among the variables in all the three equations shows the presence of at least a one directional Granger-causality and lagged error-correction term. Belloumi (2014) explains that Granger causality can be identified and checked using the VEC model which is derived from the long-run cointegration vectors. Besides, the VEC model can also help identify between short-run and long-run Granger causality. As is stipulated by Belloumi (2014), Odhiambo (2009), and Narayan and Smyth (2006) the F-test and the explanatory variables can show the presence of a short-run causal effect while the significance of the t-test of the error correction term indicates a long-run causal relationship. Hence, we obtain the short-run dynamic parameters by estimating the VEC model associated with the long-run estimates. This is specified as follows:

The VEC model's representation for Ethiopian's passenger growth determinants equation can be specified as:

(4.18.7)

$$\Delta \ln Ye_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Ye_{t-i} + \sum_{i-1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-i} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-i} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-i} + \sum_{i=1}^{q} \alpha_5 \Delta \ln ETAP_{t-i} + \lambda ECT_{t-1} + \varepsilon_{1t}$$

$$\Delta \ln ETAP_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln ETAP_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln Ye_{t-i} + \sum_{i-1}^{q} \alpha_{3i} \Delta \ln PCIM_{t-i} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln AXCR_{t-i} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln CROILPB_{t-i} + \lambda ECT_{t-1} + e_{1t}$$

The VEC model's representation for other airlines' passenger growth determinants equation can be specified as:

(4.18.8)

$$\Delta \ln Yo_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Yo_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \lambda ECT_{t-1} + \varepsilon_t$$

$$\Delta \ln WCPI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln WCPI_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln Yo_{t-i} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln CROILPB_{t-1} + \lambda ECT_{t-1} + \varepsilon_{2t}$$

The VEC model's representation of Ethiopian's air freight cargo growth determinants equation will be:

(4.18.9)

$$\Delta \ln Yc_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln Yc_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln WCPI_{t-1} + \sum_{i=1}^{q} \alpha_{6i} \Delta \ln XEM_{t-1} + \lambda ECT_{t-1} + \varepsilon_{3t}$$

$$\Delta \ln XEM_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln XEM_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta \ln Yc_{t-i} + \sum_{i=1}^{q} \alpha_{3i} \Delta \ln PCIM_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta \ln AXCR_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta \ln CROILPB_{t-1} + \sum_{i=1}^{q} \alpha_{6i} \Delta \ln WCPI_{t-1} + \lambda ECT_{t-1} + \varepsilon_{3t}$$

where $\lambda = (1 - \sum_{i=1}^{p} \delta_i)$ is the speed of the adjustment parameter with a negative sign. $VEC_1 = (\ln Ye_{t-i} - \theta X_t)$, $VEC_2 = (\ln Yo_{t-i} - \theta X_t)$, $VEC_3 = (\ln Yc_{t-i} - \theta X_t)$ are the error correction terms for Ethiopian's passengers, other airlines' passengers, and Ethiopian's air freight cargo's growth determinants respectively.

$\theta = \frac{\sum_{i=0}^{q} \beta_i}{\alpha}$ is the long-run parameter in all the three equations.

where $\alpha_{1i}, \alpha_{2i}, \alpha_{3i}, \alpha_{4i}, \alpha_{51i}$, $\alpha_{1i}, \alpha_{2i}, \alpha_{3i}, \alpha_{4i}, \alpha_{51i}$ and $\alpha_{1i}, \alpha_{2i}, \alpha_{3i}, \alpha_{4i}, \alpha_{51i}, \alpha_{6i}$ represent the three models' coefficients of short-run dynamic convergence to long-run equilibrium respectively.

D. Pairwise Granger causality test

The F-statistics of the bounds cointegration test results confirmed that the bounds test's results are above I(1) and ensure that there is a cointegration relationship in the long-run among the variables under consideration. Next we conduct a pairwise Granger causality test. The pairwise Granger causality test of Ethiopian air transport shows the direction of the causality. Taking the conditional ARDL (p, q_1, q_2, q_3, q_4) model's equations 4.18.1, 4.18.2, and 4.18.3 the pairwise Granger causality test determines the direction of causality among the dependent and independent variable in the three equations of Ethiopian's passenger growth determinants, other airlines' growth determinants, and Ethiopian's air freight cargo growth determinants.

H_0 : No Granger- Causality vs H_1 : null hypothesis is not true.

The decision criteria: we reject the null hypothesis if the p-value is ≤ 0.05.

5. Empirical Results

5.1 Unit Root test's results

One of the major problems encountered in studying economic relationships is the likelihood of spurious regressions which require testing and stationarity. The order of integration of the variables in this study is determined using unit root tests. Stationarity tests at both level and first difference were conducted using the Augmented Dickey-

Fuller (ADF) and Phillips-Perron (PP) tests. The test results are given in Table 4.2 and Table A4.1 in Appendix 4.1.

Table 4.2. Augmented Dickey-Fuller (ADF) unit root test's results

Variable	At level		First difference		Order of Integration
	Intercept (p-value)	Intercept and Trend (p-value)	Intercept (p-value)	Intercept and Trend (p-value)	
lnYe	0.9982	0.6977	0.0002	0.0003	I(1)
lnYo	0.7961	0.0870	0.0000	0.0000	I(0)
lnYc	0.9705	0.5536	0.0001	0.0001	I(1)
Lnetap	0.6146	0.0309	0.2197	0.4411	I(0)
lnIndoutput	0.0852	0.0047	0.0081	0.0210	I(0)
Ln Tourist	0.9965	0.5844	0.0004	0.0013	I(1)
LnRGDP	0.9999	0.6661	0.0000	0.0000	I(1)
LnPCIM	0.9971	0.6609	0.0373	0.0508	I(1)
LnWCPI	0.9424	0.7091	0.0016	0.0085	I(1)
lnCROILPB	0.7599	0.0703	0.0009	0.0005	I(0)
LnXEM	0.9366	0.7004	0.0185	0.1597	I(1)
LnAXCR	0.6405	0.1371	0.0041	0.0183	I(1)

Source: Author's calculations based on data from the Ethiopian Airlines Group and EAE, MoF, and NBE (1988-2018).

As shown in Table 4.2, the Augmented Dickey-Fuller test's results implies that seven variables are stationary at first difference and four variables are stationary at level.

For dealing with this problem it is crucial to check if the variables are stationary at level and first difference. The first step in a cointegration analysis is studying the order of integration of the variables under consideration. The conducted unit root tests both at level and first difference show that almost all the variables except one have a unit root in their level and thus the remaining have to be differenced to achieve stationarity. Both the Augmented Dickey-Fuller and Phillips Perron tests (see Appendix A4.1) show that the variables are integrated of different orders of I(0) and I(1) and this confirms that the ARDL model is an appropriate model specification.

5.2 Estimation of long-run OLS and SUR models

Estimation of OLS and a corresponding SUR system was done which made it possible to assess the long-run effects of the variables under considerations. The estimated results of SUR are almost the same as the OLS estimates, but the absolute value of the parameter in OLS has a relatively higher value while in case of SUR the standard error reduces in comparison to OLS' estimates. The details of the analysis are provided in separate tables (Table 4.3-4.9) considering the three equations in both OLS and SUR models' estimations.

5.2.1 OLS estimation

Taking the first difference of the dependent and independent variables for stationarity, the OLS estimation method was applied to the three equations and the estimation results are presented in Table 4.3.

Table 4.3. Estimation of Ethiopian's (ET) passengers, other airlines' passengers, and freight cargo's growth determinants estimated using OLS

Explanatory variables	Log of ET. airlines ADD passengers (Ye)	Log of other airlines ADD passengers (Yo)	Log of ET. airlines air freight cargo (Yc)
Dlog of per capita income	1.0853** (0.432)	0.3414*** (0.094	-
Dlog of ET Average price	0.0313 (0.460)	-	-
Dlog of average exchange rate	0.8750 (0.6569)	-1.1252*** (0.199)	-0.4703 (0.478)
Dlog of crude oil price in birr	-0.1298(0.456)	0.5461*** (0.118)	0.1777 (0.255)
Dlog of world CPI	-	1.1182 (0.729)	-2.4209* (1.200)
Dlog of real GDP	-	-	2.8932*** (0.324)
Dlog of import and export	-	-	-0.5129** (0.249)
Constant term	-0.0753	1.2509 (1.074)	-18.0540*** (2.588)
R2 adjusted	0.3103	0.9833	0.9277
Prob > F	0.0469	0.0000	0.0000
Number of obs.	30	30	30

Note: *, **, and *** show a 10 %, 5%, and 1 % level of significance.

A. Ethiopian's passenger growth determinants (OLS result)

As shown in Table 4.3, the explanatory variables collectively explain 31 percent of the variations in Ethiopian's passenger growth (lnYe). A test for the joint significance of the explanatory variables shows that the explanatory variables are jointly significant at the 5 percent level of significance. They explain the variations in Ethiopian's passenger growth. Among the specified explanatory variables, the log of per capita income is significant at the 5 percent level. This shows that a 1 percent change in per capita income (lnPCIM) results in a 1.085 percent change in the Ethiopian's passenger demand, other things remaining constant.

Other variables such as log of crude oil prices in Birr (lnCROILPB), log of average price per passenger (lnETAP), and log of average exchange rate (lnAXCR) were not found to be statistically significant.

B. Other airlines' passenger growth determinants (OLS result)

The model for other airlines' passenger growth was estimated using variables at their first difference stationarity. The explanatory variables collectively explain 98.3 percent of the variations in other airlines' passenger growth determinants (lnYo). A test for the joint significance of the explanatory variables shows that the explanatory variables are jointly significant at the 1 percent significance level in explaining other airlines' passenger growth determinants.

As given in Table 4.3 the parameter estimates' results show that a 1 percent change in the log of per capita income (lnPCIM) results in a 0.341 percent change in the log of other airlines' passenger demand, other things remaining constant. A 1 percent change in the average exchange rate (lnAXCR), on the other hand, results in a 1.125 percent change in other airlines' passenger growth demand in the opposite direction. Similarly, a 1 percent change in crude oil prices (lnCROILPB) results in a 0.546 percent change in other airlines' passenger growth in the same direction while the remaining explanatory variables such as the world consumer price index (lnWCPI) are found to be statistically insignificant.

C. Ethiopian air freight cargo's growth determinants (OLS result)

In the Ethiopian air freight cargo's growth determinant equation, the explanatory variables collectively explain 92.8 percent of the variations in Ethiopian's air freight cargo (lnYc) growth. A test for the joint significance of the explanatory variables shows that the explanatory variables are jointly significant at the 1 percent significance level.

The parameter estimates for log of real GDP (lnRGDP), log of the world consumer price index (lnWCPI), and log of imports and exports of goods and services (lnXEM) are significant at the 1 percent, 10 percent, and 5 percent levels respectively. The estimation results show that a 1 percent change in lnRGDP results in a 2.893 percent change in Ethiopian's air freight cargo growth, other things being constant. On the other hand, a 1 percent change in the world consumer price index (lnWCPI), is associated with a 2.421 percent change in Ethiopian's air freight cargo growth in the opposite direction. Similarly, a 1 percent change in the volume of exports and imports of goods and services is also directly related to a 0.513 percent change in Ethiopian's air freight cargo growth in the opposite direction with an unexpected sign. The rationale for such a significant unexpected sign is that other modes of freight cargo transport can substitute air freight cargo. While the remaining variables such as average exchange rate (lnAXCR) and crude oil prices (lnCROILPB) are statistically insignificant.

5.2.2 SUR estimation

With the intention of increasing the model's efficiency, the SUR estimation was done for the air transport's growth determinant model. Similarly, a correlation between the three equations were estimated and their correlation results were insignificant (see Table 4.4). This implies that since the p-value is 0.3705 we cannot reject the null hypothesis that there is no correlation in the error structures between the three different equations. The null hypothesis states that there is no correlation across equations. So, the SUR estimation results are mainly presented for a simple comparison with OLS' estimations.

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Table 4.4. Correlation matrix of residuals of the SUR method

Dependent variables	lnYe	lnYo	lnYc
Log of Ethiopian's passengers (lnYe)	1.0000		
Log of other airlines' passengers (Yo)	0.2411	1.0000	
Log of Ethiopian's air freight cargo (Yc)	0.0099	0.1947	1.0000

Note: Breusch-Pagan test of independence: chi2 (3) = 2.884, Pr = 0.4098.

Following the Breusch-Pagan test of independence, the SUR regression method is estimated and the results are presented in Table 4.5.

Table 4.5. Estimation of Ethiopian's passenger, other airlines' passenger, and freight cargo's growth determinants using the SUR method

Explanatory variables	Log of Ethiopian ADD passengers	Log of Other air-lines passengers	Log of Ethiopian air freight cargo
Dlog of per capita income	1.0294*** (0.391)	0.3312*** (0.085)	-

Dlog of ET average price	-0.1172 (0.416)	-	-
Dlog of average exchange rate	0.9875* (0.593)	-1.1376*** (0.181)	-0.4242 (0.420)
Dlog of crude oil prices in Birr	-0.1567 (0.195)	0.5523*** (0.107)	0.1474 (0.224)
Dlog of world CPI	-	1.1459*(0.664)	2.3576** (1.057)
Dlog of real GDP	-	-	2.8783*** (0.286)
Dlog of imports and exports	-	-	-0.4904** (0.217)
Cons	-0.0580 (0.066)	1.2176(0.977)	-18.06*** (2.284)
Parameters	4	4	5
R2 adjusted	0.3056	0.9833	0.9276
Prob > F	0.0139	0.0000	0.0000

Note: *, **, and *** show a 10 %, 5%, and 1 % level of significance.

Source: Author's calculations based on data from the Ethiopian Airlines Group and EAE, MoF, and NBE (1988-2018).

A. Ethiopian's passenger growth determinants (SUR's results)

The three regression models are treated as SUR. The R^2 shows that all the three models have strong model fit properties. And the chi2 results show that each of the three models is also statistically significant. For the log of Ethiopian's passenger growth (lnYe) equation, a 1 percent change in PCIM results in a 1.029 percent change in Ethiopian's passenger growth in the same direction, ceteris paribus. A 1 percent change in the average exchange rate (lnAXCR) results in a 0.899 percent change in Ethiopian's passenger growth, other things remaining constant with an unexpected sign. This shows that an increase in aggregate demand outweighs the effect of an increase in the exchange rate that is forced to complement the passenger growth demand than showing an inverse relationship. The other two explanatory variables (lnETAP) and (lnCROILPB) are statistically insignificant.

B. Other airlines' passenger growth determinants (SUR's result)

In the second equation, other airlines' passenger growth determinants were estimated and it was found that log of per capita income (lnPCIM) and log of average exchange rate (lnAXCR) were statistically significant at the 1 percent level as expected. While the log of crude oil prices (lnCROILPB) and log of the world consumer price index (lnWCPI) were statistically significant at the 1 percent and 10 percent significance levels respectively with unexpected signs. Moreover, the estimation results showed that a 1 percent change in per capita income (lnPCIM) resulted in a 0.331 percent change in other airlines' passenger growth, ceteris paribus, with the effect in the same direction.

Similarly, a 1 percent change in the average exchange rate (lnAXCR) had a direct effect of a 1.138 percent change in other airlines' passenger growth but in the opposite direction.

On the other hand, a 1 percent change in crude oil prices (lnCROILPB) was associated with a 0.577 percent change in other airlines' passenger growth (lnYo) and a 1 percent change in the world consumer price index resulted in a 1.146 percent change in other airlines' passenger growth. Since the aggregate demand for air transport is higher the negative impact of an increase in crude oil prices and the world consumer index a cumulative effect on other airlines' passenger growth demand increased with oil prices and the world consumer price index with different degrees of significance.

C. Ethiopian's air freight cargo's growth determinants (SUR's results)

The last equation of the model is Ethiopian's air freight cargo's growth determinants. In this equation only real GDP was statistically significant at the 1 percent significance level with an expected sign. Accordingly, a 1 percent change in real GDP (lnRGDP) was highly related to a 2.848 percent change in Ethiopian's air freight cargo's (lnYc) growth in the same direction. Log of imports and exports of goods and services (lnXEM) led to a 1 percent increase in the imports and exports of goods and services resulting in a 0.490 percent decrease in Ethiopian's air freight cargo's growth, ceteris paribus. A 1 percent increase in the world consumer price index (lnWCPI) was associated with a 2.358 percent increase in Ethiopian air freight cargo (lnYc). In this equation, the variables crude oil prices and average exchange rate were statistically insignificant.

5.3 Bounds cointegration test

The bounds cointegration test was based on the F-test statistics under the null hypothesis that there is a no cointegration relationship. Taking the lag order selection criteria, the lag choice of the model is lag order p and q, ARDL (2,0,2). Thus, the model specified as Ethiopian's air freight cargo and other airlines' passenger movements are appropriate as the selected maximum lag order of two (2) while in the model specified as Ethiopian's passenger movements, the variables are most fitted and significant with lag order ARDL (1,0,2).

For determining the long-run and short-run relationships between the variables, the cointegration test's results for the bounds test proposed by Pesaran et al. (2001) are given in Table 4.6. The values of F-statistics obtained from the bounds tests are (10.35), (6.037), and (8.67) for the three equations. Hence, we strongly reject the null hypothesis of no cointegration/long-run relationship at the 1 percent and 5 percent significance levels. This shows that Ethiopian's passenger growth, other airlines' passenger growth, and air freight cargo transported through Addis Ababa Airport had a long-run relationship with their respective explanatory variables.

The explanatory power of the independent variables is assessed using the coefficient of determination (R2 adjusted). The results show that about 80.45 percent, 88.68 percent, and 87.30 percent of the variations in Ethiopian's passengers, other airlines' passengers, and air freight cargo transported through Addis Ababa Airport are explained by the explanatory variables in the models. The fits of the models measured in R2 values are given in the lower half of Tables 4.7-4.9 LR and SR ARDL tabular presentations.

Table 4. 6. Bounds cointegration test's results

Equations/ Dependent variables	F-statistic values	Significance level	Bound test Min I(0)	Bound test Max I(1)
$F(Ye/PCIM, AXCR, CROILPB, ETAP)$	10.35	2.5%	2.88	3.87
		1.0%	3.29	4.37
$F(Yo/PCIM, AXCR, CROILPB, WCPI)$	6.037	2.5%	2.88	3.87
		1.0%	3.29	4.37
$F(Yc/RGDP, AXCR, CROILPB, WCPI, XEM)$	8.67	2.5%	2.70	3.73
		1.0%	3.06	4.15

Note: Lower and upper-bound critical values are taken from Pesaran et al. (2001).

Source: Author's calculations based on data from the Ethiopian Airlines Group and EAE, MoF, and NBE (1988-2018).

Hence, the appropriate estimation techniques in the case of the three equations are the ARDL and VEC models. This is confirmed by estimating the long-run model with the VEC model and the short-run model which is the ARDL model. This shows that even if there are shocks that have an effect in the short-run, they will converge in the long-run. In other words, since the series are cointegrated, they are related to each other and have a long-run relationship and can be combined in a linear fashion. Once the model has been specified as the ARDL model, the next step is analyzing and interpreting the long-run and short-run relationships of the specified models.

5.4 Estimation of long-run and short-run dynamics using the ARDL approach

5.4.1 Ethiopian's passenger growth determinants

The major determinant factors in the growth of the air transport sector in general and Ethiopian's passenger growth in particular were analyzed taking selected annual macro-variables such as per capita income, average exchange rate USD versus ETB, crude oil prices in ETB, and Ethiopian's average airfare/price covering the period 1988-2018 or 31 years. ARDL's long-run form and bounds test's results of the level equation in Table 4.7 show the existence of the long-run effect of the model while the ARDL and VEC regressions show the short-run estimation of the models. Both short-run and long-run estimations are given in Table 4.7 where the ARDL model is estimated using ARDL (2,0,0,0,2). The determinant factor of passenger growth both in the short-run and long-run is also given in Table 4.7.

Table 4.7. Estimation of Ethiopian's passenger growth determinants (LR, SR, and VEC)

Ethiopian airlines passengers (Ye) Difference equation	Short-run Coefficient	Prob.	Level equation	Long-run Coefficient	Prob.
D(LnAXCR)	0.7571*** (0.164)	0.0002	lnPCIM	0.5921***(0.068)	0.0000
D(LnCROILPB)	0.0686 (0.071)	0.3447	lnAXCR	-0.3966**(0.146)	0.0130
D(LnCROILPB(-1))	-0.08546*(0.044)	0.0641	lnCROILPB	0.4114*** (0.072)	0.0000
CointEq(-1)*	-0.9904***(0.096)	0.0000	lnETAP	-0.3355**(0153)	0.0404
			Cons	4.223(0.068)	0.0000

Cointeq=lnYe-(-0.3355*lnETAP+0.4114*lnCROILPB -0.3966*lnAXCR+0.5921*lnPCIM+4.2238)

R2 0.8045%, Adjusted R2 0.7810%, Log likelihood (61.194), Durbin-Watson stat (2.117), Akaike info criterion (-3.944), Schwarz criterion (-3.756) and Hannan-Quinn criterion (-3.885)

Note: *, **, and *** show a 10 %, 5%, and 1 % level of significance.

It is found that in the long-run real per capita income effected Ethiopian's passenger movements positively and significantly while average airfares or average price per passenger and average exchange rate effected the number of airline passengers negatively. Except world crude oil prices all the variables in the model had the expected signs at 1 percent and 5 percent significance levels. As discussed in the theoretical and empirical literature parts of this chapter, per capita income or economic growth has a positive impact on passenger growth.

Real per capita GDP (lnPCIM) had a long-run impact on the growth in Ethiopian's passenger and was statistically significant at the 1 percent significance level. The coefficient of the parameter natural log of per capita income PCIM is 0.592. This shows that in the long-run holding other things constant, a 1 percent change in per capita incomes brings about a 0.59 percent change in Ethiopian's passenger growth in the same direction. In contrast, the average price per passenger (lnETAP) was statistically significant at the 5 percent significance level. The coefficient of average airfares or average price is -0.34. This shows that in the long-run, holding other things constant, a 1 percent increase in average air ticket prices brings about a -0.34 percent decline in Addis Ababa Airport's passenger numbers. Similarly, the average exchange rate (lnAXCR) is also statistically significant at the 5 percent significance level. The coefficient of the average exchange rate is -0.3966. This implies that in the long-run, assuming other things are constant, a 1 percent change in the average exchange rate negatively impacted Ethiopian's passenger movements by about a 0.3966 percent decline during the study period.

Among the long-run variables, the coefficient for crude oil prices (lnCROILPB) is positive and statistically significant, though the regression results are against the expected sign. Hence, positive and significant world crude oil prices or energy prices complement the relationship between air passenger movements and energy consumption. Though not directly related, Small and Van Dender (2008) too found that transport in general was relatively unresponsive to broad-based price signals. Wadud (2014, 2015) showed elasticities in air transport demand with respect to airfares, jet fuel prices, and other cost effects having imperfect reversibility. In air transport, passengers are sensitive to time, safety, and price. This can be associated with the theory of supply and demand that in the absence of a close substitute, an increase in air transport demand at the aggregate level means that passengers are increasingly using air transport despite an increase in energy prices.

Following the determination and estimation of long-run coefficients of the equations, the short-run VEC model is estimated in Table 4.7. VEC, which is a one lagged period residual obtained from the estimated dynamic short-run model refers to the speed of adjustment to restore equilibrium in the dynamic model after a shock. The coefficient of the error correction term has the expected negative sign (-0.99) and is strongly significant. This shows a high speed of adjustment to the equilibrium after a shock. Approximately 99.04 percent of the disequilibrium from the previous year's shock converges back to the long-run equilibrium in the current year. Such a highly significant VEC provides evidence of the existence of a stable long-run relationship among the variables.

In the short-run, a one lagged period world crude oil prices effect Ethiopian's passenger movements negatively. When world crude oil prices increase by 1 percent, Ethiopian's passenger movements at Addis Ababa International Airport fall by 0.08546 percent as expected. Unlike a significant long-run impact, per capita incomes have no short-run significant impact on the economy. The coefficient of the average exchange rate is positive and significant and its regression results are against the hypothesized/expected signs. Hence, for heavily import dependent economies, the relationship between aggregate transport demand and an increase in exchange rate need further study.

5.4.2 Other Airlines' passenger growth determinants

In addition to the flag carrier Ethiopian, other airlines are also providing passenger transport services at Addis Ababa Bole International Airport. The major airlines which are currently using Addis Ababa International Airport are Emirates, Fly Dubai, Gulf Air, Yemenia, Kenya Airways, Lufthansa, Egypt Air, Sudan Airways, Turkish Air, and Air China. Some of them have daily operations while others have more than once a week flights from Addis Ababa International Airport. Like Ethiopian's passenger growth determinants, identifying air transport passengers' growth determinants for the other airlines is analyzed using the long-run ARDL and dynamic short-run and VEC models. Based on the model's specification test results, log of per capita income (lnPCIM), log of the world consumer price index (lnWCPI), log of the average exchange rate (lnAXCR), and log of world crude oil prices (lnCROILPB) were considered as explanatory variables for the study period 1988-2018.

Table 4.8. Estimation of other airlines' passenger growth determinants (LR, SR, and VEC)

Other airlines' passengers (Yo)	Short-run and VEC model		Long-run		
Differenced equation	Coefficient	Prob.	Level equation	Coefficient	Prob.

D(lnPCIM)	2.4747*** (0.374)	0.0002	lnPCIM	0.3946*** (0.1505)	0.0001
D(lnWCPI)	-2.2736 (3.343)	0.5062	lnWCPI	-0.1723(1.3168)	0.7862
D(lnWCPI(-1))	8.5784*** (2.430)	0.0028	lnAXCR	-1.1910*** (0.309)	0.0000
D(lnAXCR)	-2.2184***(0.541)	0.0008	lnCROILPB	1.0626*** (0.191)	0.0000
D(lnAXCR(-1))	2.2683*** (0.597)	0.0016	Cons	3.0566**(1.973)	0.1409
D(lnCROILPB)	1.1811*** (0.222)	0.0001			
D(lnCROILPB(-1))	-0.9839*** (0.247)	0.0011			
CointEq(-1)*	-1.6786*** (0.154)	0.0000			
Cointeq	EC=lnYo-(0.3192*lnPCIM-0.1919*lnWCPI+1.0626*lnCROILPB-2.2138*lnAXCR+3.0566)				
R2 0.8868%, Adjusted R2 0.8491%, Log likelihood (31.96), Durbin-watson stat (2.14), Akaike info criterion (-1.65), Schwarz criterion (-1.27) and Hannan- Quinn criterion (-1.53)					

Note: *, **, and *** show a 10 %, 5%, and 1 % level of significance

The long-run and short-run estimations of other airlines' passenger growth determinants are given in Table 4.8 for a comparison. We begin with the long-run estimation. According to the long-run estimation of ARDL, real per capita income **(**lnPCIM) had a positive and significant effect on other airlines' passenger growth as expected. Similarly, the average exchange rate (lnAXCR) had a negative and significant effect as expected. In this model's estimation results, the world consumer price index (lnWCPI) was insignificant while other variables had the hypothesized signs at the 1 percent and 5 percent significance levels. The sign and significance of the coefficient for income per capita had a positive impact on Ethiopia's economic growth in general and on air transport growth in particular. Moreover, a continuous growth in the average exchange rate (devaluation), effected air transport's growth negatively.

The log of other airlines' passenger growth determinants function shows that holding other things being constant a 1 percent change in per capita income (lnPCIM) is associated with a long-run impact of a 0.39 percent change in the growth of other airlines' passenger movements (lnYo) in the same direction with an inelastic response. Similarly, the coefficient of the log of average exchange rate (lnAXCR) is -1.19 and is statistically significant at the 1 percent level. This implies that in the long-run, holding other things constant, a 1 percent change in the average exchange rate brought about a -1.19 percent change in other airlines' passenger movements during the study period and was highly elastic.

On the other hand, the coefficient of the log of the world consumer price index was negative as expected but statistically insignificant. In the long-run since the margin of error is higher than 10 percent, other airlines' passenger demand was not responsive to a change in the world consumer price index. The coefficient of world crude oil prices (lnCROILPB) had a positive sign and was significant at the 1 percent level. Assuming other things being constant, a 1 percent increase in the price of crude oil is associated with a 1.0626 percent change in other airlines' passenger growth in the long-run. This result is similar to the result for Ethiopian's passenger growth determinants. The rationale for such a result could be the absence of a close substitute for air transport services and simultaneously increasing aggregate passenger demand for air transport services.

Energy is the most crucial determinant of air transport services. This result is not in line with theoretical analyses that demand reduces with an increase in energy prices. Hence, positive and significant world crude oil prices complement the relationship between air passenger movements and energy consumption. Hence, the consumption effect outweighs the price effect. Small and Van Dender (2008) also found that transport demand was not responsive to broad-based price signals. In addition, some recent studies (Wadud, 2014, 2015) show elasticities of air transport demand with respect to airfares, jet fuel prices, and other cost effects having imperfect reversibility. In the transport industry passengers' preferences might vary between individual demand and aggregate demand which can be confirmed by the results of our test for the effect of energy prices on other airlines' passenger growth.

The short-run dynamics are estimated in Table 4.8, where a one-lagged period residual VEC term is obtained from the estimated dynamic short-run model associated with the speed of adjustment to restore equilibrium in the dynamic model after a shock. The coefficient of the error correction term has the expected negative sign -1.68 and is strongly significant at the 1 percent significance level. This shows that other airlines' passenger model had a very high and strong speed of adjustment to the equilibrium after an exogenous shock. The estimation results show that about a 167.86 percent disequilibrium from the previous year's shock converged back to the long-run equilibrium in the current year. Such a highly significant VEC provides evidence of the existence of a stable long-run relationship between explanatory variables and other airlines.

The short-run dynamic estimation shows that current per capita incomes, previous year's world consumer price index, current average exchange rate, and previous year's world crude oil prices are statistically significant at the 1 percent significance level as expected and had a strong relationship with other airlines' passenger movements. This shows that these variables are among the main growth determinants of other airlines' passenger movements from Addis Ababa International Airport. The estimated result shows that a 1 percent change in domestic per capita income is directly related to a 2.47 percent change in other airlines' passenger growth and movements from Addis Ababa International Airport in the same direction.

In addition, the coefficient of the world consumer price index shows that in the short-run, a 1 percent change in the previous year's world consumer price index is associated with a 8.58 percent change in other airlines' passenger growth in the short-run in the same direction with an elastic response. Similarly, estimation of the current year's average exchange rate has an inverse relation with other airlines' passenger growth. This can be expressed as: in the short-run a 1 percent change in the average exchange rate is associated with a -2.22 percent change in other airlines' passenger growth in the opposite direction. Similarly, a 1 percent change in the previous year's world crude oil prices leads to a -0.9839 percent change in the current year for other airlines' passenger growth.

The previous year's average exchange rate has a strong positive relation with other airlines' passenger growth. The estimation results show that in the short-run, a 1 percent increase in the previous year's exchange rate induced a 2.27 percent increase in other airlines' passenger growth. According to the estimation results, other airlines' passengers are highly sensitive to the current year's average exchange rate and this has an inverse relationship with the previous year's average exchange rate. Since air transport is directly affected by exchange rate, previous year's passengers have a tendency effect positively and contributed to increase using air transport services despite an increase in the average exchange rate. This show's that the previous year's exchange rate has a positive impact on aggregate demand among other airlines' passengers.

The last determinant variable is world crude oil prices. The short-run estimation results show that a 1 percent change in the current year's world crude oil prices is directly associated with a 1.18 percent change in other airlines' passenger growth in the current year. Current year's world crude oil prices have impact other airlines passenger positively which is against economic demand theory while the previous year's world crude oil prices have impacted passenger growth negatively. The current year's world crude oil prices have a similar sign and significance for the long-run and short-run effects on other airlines' passenger growth. This shows that the complementary effect of current world crude oil prices is higher than its substitution effect and hence, other airlines' passenger demand for air transport services increases with energy prices.

5.4.3 Freight Cargo transportation at Addis Ababa International Airport

Ethiopian's cargo and logistics service, a unit of the Ethiopian Airlines Group, is providing transport services for large quantities of imported and exported goods. In a landlocked country like Ethiopia, the air transport industry plays a significant role which is crucial for perishable materials. As shown by many other studies, a growth in air transport services plays a significant role in the growth of the economy and similarly a growth of the economy also plays a significant role in the growth of the air transport sector. In addition, there are many other variables which have a significant impact on the growth of air transport. The growth determinants of Ethiopian's air freight cargo considered in this study include real GDP, the world consumer price index, average exchange rate, world crude oil prices, and volume of total imports and exports of goods and services. The estimation results of the long-run autoregressive lag model, short-run dynamics, and the VEC model are given in Table 4.9.

Table 4.9. Estimation of Ethiopian's air freight cargo growth determinants (LR, SR, and VEC)

Ethiopian's air freight cargo (Yc)	Short-run and ECM model			Long-run	
Differenced equation	Coefficient	Prob.	Level equation	Coefficient	Prob.
D(lnYc(-1))	0.2867**(0.104)	0.0172	lnRGDP	2.8048***(0.432)	0.0000
D(lnRGDP)	2.1414***(0.374)	0.0002	LnWCPI	-1.4821 (2.044)	0.4822
D(lnWCPI)	0.1294 (1.640)	0.9384	LnAXCR	-1.4967* (0.756)	0.0712
D(lnWCPI(-1))	-3.9750***(1.487)	0.0203	LnCROILPB	0.6479** (0.291)	0.0460
D(lnAXCR)	-0.2946(0.321)	0.3773	LnXEM	-0.9894***(0.309)	0.0076
D(lnAXCR(-1))	1.5169*** (0.338)	0.0007	Cons	-11.366***(3.65)	0.0089
D(lnXEM)	-0.2257 (0.239)	0.3641			
D(lnXEM(-1))	1.2170***(0.274)	0.0008			
D(lnCROILPB)	-0.0378 (0.144)	0.7974			
D(lnCROILPB(-1))	-0.6526*** (0.158)	0.0014			
CointEq(-1)*	-1.3646*** (0.143)	0.0000			

Cointeq EC=LnYc-(2.8049*LnRGDP-1.4822*LnWCPI+0.6480*LnCROILPB-0.9894*LnXEM-1.4967*LnAXCR-11.3666)
R2=0.8730, Adjusted R2=0.8025, Log likelihood=54.02583, Durbin-Watson stat =1.927929, Akaike info criterion=-2.967299, Schwarz criterion=-2.448669 and Hannan-Quinn criterion=-2.804870

Note: *, **, and *** show a 10 %, 5%, and 1 % level of significance

Based on the model test's results, log of real gross domestic product (lnRGDP), the world consumer price index (lnWCPI), average exchange rate (lnAXCR), world crude oil prices (lnCROILPB), and average exchange rate (lnXEM) were considered as explanatory variables.

As shown in Table 4.9 the estimation results of real gross domestic product (lnRGDP), and average exchange rate (lnAXCR) have a long-run causal relation with Ethiopian's air freight cargo growth. Accordingly, in the long-run, a 1 percent change in GDP is highly related to a 2.80 percent change in the growth of Ethiopian's freight cargo in the same direction. Similarly, a 1 percent change in the average exchange rate is directly related to a -1.50 percent change in air freight cargo services in the opposite direction.

Other determinant variables such as log of crude oil prices (lnCROILPB) and total annual volume of imports and exports of goods and services (lnXEM) were significant at the 1 percent and 5 percent significance levels with unexpected signs. This is interpreted to mean that in the long-run, holding other things constant, a 1 percent change in world crude oil prices results in an increase in air freight cargo by 0.65 percent in the same direction. Similarly, a 1 percent change in the log of imports and exports of goods and services brings about a -0.99 percent change in air freight cargo's growth. On the one hand, the price of crude oil is continuously increasing due to various factors including the exchange rate effect. Likewise, the aggregate demand for Ethiopian's air freight cargo is also increasing. If the aggregate demand for air freight cargo is higher than the oil price effect, then in the long-run crude oil prices play a complementary role in Ethiopian's freight cargo growth. Moreover, the negative estimation result of imports and exports of goods and services shows that in the long-run Ethiopian's air freight cargo can be substituted by other modes of transport.

Further, the short-run dynamic and VEC models of air freight cargo equations are also shown in Table 4.9. The VEC model shows that a one period lagged residual is obtained from the short-run dynamic model's estimation. This shows the speed of adjustment reverts back to the long-run equilibrium level in the short-run after a shock. Thus, the estimation result of the cointegrating coefficient of the VEC model is -1.3646 implying an approximately 136.46 percent disequilibrium that results from a previous year's shock which can be converged back to the current year's long-run equilibrium. This result is strongly significant at the 1 percent significance level. This means that the model reverts back to equilibrium in less than one period which is a year in this study. This confirms the existence of a stable long-run relationship among the variables.

The short-run dynamics estimation model considered rate of changes in the variables are shown in Table 4.9 such as (D(lnYc(-1)), D(lnRGDP), D(lnWCPI), D(lnWCPI(-1)), D(lnAXCR), D(lnAXCR(-1)), D(lnXEM), D(lnXEM(-1)), D(lnCROILPB) and D(lnCROILPB (-1)) are growth determinants of Ethiopian air freight cargo in the current year with different economic implications.

The coefficient of the log of a one lagged period air freight cargo D(lnYc(-1)) is positive and significant at the 5 percent significance level. This shows that in the short-run a 1 percent change in the previous year's air freight cargo induced a 0.29 percent change in the log of Ethiopian's air freight cargo growth in the same direction. This further shows the existence of a short-run causal relationship between current and previous year's air freight cargo. Similarly, the log of real gross domestic product D(lnRGDP) is significant at the 1 percent significance level. This shows that in the short-run a 1 percent increase in real GDP leads to a 2.14 percent increase in air freight cargo's growth. This also implies that real GDP and air freight cargo have a short-run relationship. The last variable with a positive expected result which is statistically significant at the 1 percent level is D(lnXEM (-1)). Accordingly, the results show that in the short-run a 1 percent change in the previous year's imports and exports of goods and services brings about a 1.22 percent change in air freight cargo's growth in the same direction.

In addition, the coefficient of the log of previous year's world consumer price index D(lnWCPI(-1)) is negative and strongly significant indicating that a 1 percent increase in the previous year's world consumer price index is associated with a -3.97 percent decrease in air freight cargo's growth in the opposite direction. The nature of responsiveness is elastic and has flipped the direction of the causal relationship among these variables in the short-run. Similarly, the log of previous year's crude oil prices

D(lnCROILPB(-1)) has a negative and strong causal relation with air freight cargo's growth. This means that holding other things constant a 1 percent change in the previous year's crude oil prices is directly related to a -0.65 percent change in air freight cargo's growth.

The remaining determinant variable is the previous year's average exchange rate D(lnAXCR (-1)) which is significant at the 1 percent significance level. The estimation results show that previous year's exchange rate has a positive causal relation with the current year's air freight cargo indicating that a 1 percent change in the previous year's average exchange rate results in a 1.52 percent change in air freight cargo's growth in the short-run in the same direction. It is expected that currency devolution favors domestic products and discourages imported goods. However, for countries having limited domestic manufacturing goods such an unexpected sign implies that the previous year's devolution of the currency leads to an increase in the current year's trade and air freight cargo goods and services.

5.5 Pairwise Granger causality

The nature of the relationship between air transport and economic growth including other macroeconomic determinant factors can be analyzed using the Granger causality tests. Estimation of pairwise Granger causality as shown in Table 4.10 was regressed by taking each variable as the dependent variable and it was found that when Ethiopian's passenger growth determinants were the dependent variables per capita income Granger caused growth in the airline's passengers. Similarly, when per capita income was the dependent variable it Granger caused Ethiopian's passenger growth and Ethiopian's passenger growth Granger caused per capita incomes. This implies that per capita income and passenger growth have a long-run bi-directional causality (from per capita income to passenger growth and vice-versa). Among the given variables in Equation 4.1, average airfares Granger caused the average exchange rate, per capita income Granger caused the average exchange rate and average airfares. They have unidirectional causality when the dependent variable is Ethiopian's passenger growth, per capita income, and average airfares respectively.

In the Granger causality test each variable considered as the dependent variable and the remaining as independent variable. The estimation results of other airlines' passenger growth determinants and per capita income as the dependent variables show that other airlines' passenger and per capita income and other airlines' passenger growth and average exchange rate have unidirectional causal relationships. In this equation, crude oil prices have bi-directional causal relationships with the average exchange rate and average exchange rate has a bi-directional causal relationship with the consumer price index.

The pairwise Granger causality tests shown in Table 4.10 implies that crude oil prices with the world consumer price index as well as average exchange rate with world consumer price index have bidirectional causality. The remaining others have unidirectional causal relationships (such as real gross domestic product with Ethiopian air freight cargo, crude oil price with Ethiopian air freight cargo, average exchange rate with Ethiopia air freight cargo, etc.).

Table 4.10. Pairwise Granger causality test's results.

Dependent variables	Granger Causality	Regressions' t-statistics (LR)	VEC t-stat.	Granger causality
Ethiopian, per capita income, and airfare as dependent	PCIM causes Ethiopian and vice-versa	cointegrated	Significant	Bidirectional
	Airfare prices cause exchange rate	cointegrated	Significant	Unidirectional
	PCIM cause exchange rate	cointegrated	Significant	Unidirectional
	PCIM cause air fares	cointegrated	Significant	Unidirectional
Other airlines' and per capita income are tested as dependent	Other airlines cause PCIM	cointegrated	Significant	Unidirectional
	Other airlines cause exchange rate	cointegrated	Significant	Unidirectional
	Crude oil prices cause world CPI and vice-versa	cointegrated	Significant	Bidirectional
	Exchange rate cause world CPI and vice-versa	cointegrated	Significant	Bidirectional
Air freight cargo and RGDP as dependent	RGDP cause air freight cargo	cointegrated	Significant	Unidirectional
	World CPI cause air freight cargo	cointegrated	Significant	Unidirectional
	Crude oil prices cause air freight cargo	cointegrated	Significant	Unidirectional
	Imports and exports cause air freight cargo	cointegrated	Significant	Unidirectional
	Exchange rate cause air freight cargo	cointegrated	Significant	Unidirectional
	Crude oil prices cause imports and exports	cointegrated	Significant	Unidirectional
	Crude oil prices cause world CPI and vice-versa	cointegrated	Significant	Bidirectional

	Exchange rate cause world CPI and vice-versa	cointegrated	Significant	Bidirectional
	Crude oil prices cause imports and exports	cointegrated	Significant	Unidirectional
	Exchange rate cause imports and exports	cointegrated	Significant	Unidirectional

Sources: Author's description based on pairwise Granger causality tests.

The results percentage have a long-run cointegration and a significant error correction as identified in the first, second, and third equations in Table 4.10. They make a significant contribution to their respective directions of causality.

5.6 Model diagnostic and stability tests

After estimating the long-run and short-run models, the model's stability and diagnostic tests were done. The tests include functional form (Ramsey's RESET), normality test (Jaque-Bera test based on a test of skewness and kurtosis of residuals), a serial correlation test (Brush and Godfrey LM test for autocorrelation), and heteroscedasticity test (based on the regression of squared residuals on squared fitted values). The results are reported in Table 4.11.

Table 4.11. Results of Diagnostic Tests

Models or equations	Serial Correlation test: Breusch-Godfrey LM		Heteroscedasticity test: Breusch-Pagan-Godfrey		Normality test: Jaque-Bera	
	Prob. F-value	Prob. Chi-Square (2)	Prob. F-value	Prob. Chi-Square (2)	Jarque-Bera	Probability
lnYe	0.3260	0.1830	0.1550	0.1594	3.1589	0.2060
lnYo	0.6029	0.3638	0.8474	0.7437	1.0716	0.5852
lnYc	0.9529	0.8701	0.3954	0.3419	0.2396	0.8870

As can be seen in Table 4.11 the abbreviations (lnYe, lnYo and Yc) are equations representing Ethiopian's passengers, other airlines' passengers, and air freight cargo transported from and to Addis Ababa Bole International Airport. A robustness test was done for air transport's growth determinant. Serial correlated error, heteroscedasticity, and normality tests are suggested to ensure that the model is serially independent, homoscedastic, and normally distributed.

The p-value associated with the F-test's statistics was unable to reject the null hypothesis specified for each test with all the three equations specified as follows:

i) The null hypothesis for the Breusch-Godfrey serial correlation LM test (Ho: no serial correlation) cannot be rejected in the three equations since the p-value associated with the test statistics is greater than the standard significant level (0.1830>0.05, 0.3638>0.05, and 0.8701> 0.05) for the three services.

ii) The null hypothesis for the Breusch-Pagan-Godfrey heteroscedasticity test (Ho: no heteroscedasticity) cannot be rejected in the three equations since the p-value associated with the test statistics is greater than the standard significance level (0.1594>0.05, 0.7437>0.05, and 0.3419>0.05).

iii) The last diagnostic test is the Jaque-Berra normality test, with the null hypothesis that the residuals are normally distributed. The null (0.2060, 0.5852, and 0.8870) cannot be rejected at the 5 percent level of significance in the three equations (see also Figures A4.1a, A4.2a, and A4.3a in Appendix A4).

The estimated ARDL model is checked for various diagnostic and model stability tests and it proves to be well-specified. In addition, the parameter stability of the models is checked using the cumulative sum (CUSUM) and its squares. The variables' forecasting ability are very good and progressively increasing. As can be seen in the (Figure A4.1 - 4.3) the estimated coefficients are also stable.

5.7 Summary of the estimation results of the alternative models

In an analysis of Ethiopian air transport, the growth determinant factors were examined through various model estimation techniques. Following the stationarity test ADF and PP, the long-run relationship of the model was also tested using the bounds cointegration test techniques. Based on the cointegration test, the results of the F-statistics for the three equations namely Ethiopian's passengers, other airlines' passengers, and Ethiopian's air freight cargo were above the upper bound that confirmed the existence of a long-run relationship between their respective explanatory variables. In addition, the OLS and SUR models were also used as a comparison to see the significance trends of the determinant variables.

Table 4.12. Summary significance of estimated alternative models

Equation 1. Ethiopian's passengers						
Explanatory variables	Other models		ARDL Model			
	OLS	SUR	SR	LR	VEC	Causality

Per capita income	Signif.(+)	Signif.(+)	No SR	Signif.(+)	Signif.	Bidir.
Average exchange rate		-	Signif.(+)	Signif.(-)	Signif.	No
Crude oil prices	-	-	Signif.(-)	Signif.(+)	Signif.	No
Airfares	-	-	Signif.(-)	Signif.(-)	Signif.	Unidir.
Equation 2. Other Airlines' passengers						
Per capita income	Signif.(+)	Signif.(+)	Signif.(+)	Signif.(+)	Signif.	Unidir.
Average exchange rate	Signif.(-)	Signif.(-)	Signif.(+/-)	Signif.(-)	Signif.	Bidir.
Crude oil prices	Signif.(+)	Signif.(+)	Signif.(+/-)	Signif.(+)	Signif.	No
CPI	-	Signif.(+)	Signif.(+/-)	Insignif.	Signif.	Bidir.
Equation 3. Ethiopian's air freight cargo						
RGDP	Signif.(+)	Signif.(+)	Signif.(+)	Signif.(+)	Signif.	Unidir.
Average exchange rate	-	-	Signif.(+/-)	Signif.(-)	Signif.	Bidir.
Crude oil prices	-	-	Signif.(+/-)	Signif.(+)	Signif.	Bidir.
CPI	Signif.(-)	Signif.(+)	Signif.(+/-)	Insignifi.	Signif.	No.
Imports and exports	Signif.(-)	Signif.(-)	Signif.(+)	Signif.(-)	Signif.	Unidir.

Sources: Author's description of the summary of various models' estimation results.

Table 4.12 gives a comparison of the estimation results based on their significance levels. For instance, per capita income was significant in the OLS and SUR estimation methods. Since the focus of this research is ARDL and VEC models, the ARDL estimation results showed that national per capita income only had a long-run effect but in the long-run it had a significant effect and a bi-directional relationship with Ethiopian passenger growth. Other things remaining constant, in the long-run Ethiopian's passenger growth will have positive and significant effect and economic growth in the country will also have a significant role in supporting air transport's growth.

On the other hand, the estimation results for the national per capita income and the other airlines' growth are similar but have a long-run and short-run effect in one direction only (per capita income to other airlines' passengers). This shows that as economic activities increase, air transport activities also increase both in the short-run and long-run. This means that the effect of other airlines' passenger growth on economic activities is not significant both in the short-run and in the long-run. In the third equation, real GDP was estimated and found significant in the OLS, SUR, and short-run and long-run ARDL methods with unidirectional causality (real GDP to air freight cargo). This means that gross domestic product has a significant role in the overall growth of the economy both in the short-run and long-run but not vice-versa. Though Ethiopia is a landlocked country, the volume of air freight cargo imported and exported is not significant enough to affect the economy.

Other determinant variables considered in Table 4.11 were significant for air transport's growth both in the short-run and long-run with imperfect reversible and causal relationships. For instance, world crude oil prices and average exchange rate had a unidirectional causal effect on other airlines' passenger and air freight cargo growth. In other words, crude oil prices versus world CPI and exchange rate versus world CPI had bi-directional causal relations with each other in both other airlines' and air freight cargo equations.

6. Summary, Conclusion, and Recommendations

In this study, the determinants of Ethiopian air transport's growth were explained by differentiating them between annual passenger growth determinants and air freight cargo growth determinants. Passenger growth was further segmented into Ethiopian and other airlines' passenger growth. The Augmented Dickey-Fuller and Phillips-Perron tests as well as the bounds cointegration tests' results confirmed that the autoregressive distributed lag (ARDL) and vector error correction (VEC) models are appropriate model specifications. Accordingly, the growth determinants of Ethiopian air transport were analyzed using dynamic short-run and long-run ARDL and VEC models. In addition, OLS and SUR estimation methods were also used for comparing the effects and significance of the variables.

The important variables in the three equations using annual data are annual air transport passengers (Ethiopia and other airlines) and air freight cargo treated as the dependent variables. While Ethiopian's average airfares (price per passenger), national per capita income, real gross domestic product, average exchange rate, the world consumer price index, crude oil prices, and volume of imports and exports were explanatory variables covering the period 1988-2018.

The results showed that national per capita income had a positive and significant short-run (0.3946 percent) and long-run (2.4747 percent) causal relationship with other airlines' passenger growth. In the case of Ethiopian's passenger growth, per capita income only had a long-run (0.5920 percent) positive and significant effect. As compared to the national per capita income, real GDP best explains Ethiopian's air freight cargo growth. This shows that the coefficients of real GDP had short-run (2.1414 percent) and long-run (2.8048 percent) causal effects on the growth of Ethiopian's air freight cargo with a high elastic response. This finding is consistent Mukkala and Tervo (2012) and Mehmood and Shahid's (2014) findings who found strong long-run relationship between air transport growth and economic growth. Moreover, OLS' estimation results of real GDP (2.8783) had a relatively higher causal effect on the growth of air freight cargo than the short-run and long-run ARDL models.

Ethiopian's average price per passenger had a long-run inverse relationship with the Ethiopian passengers' growth. Unlike in the long-run, the average price per passenger had no short-run effect on passenger growth. In this study, the world consumer price index was considered as the growth determinant of other airlines' and air freight cargo's growth. Accordingly, the OLS and ARDL models were estimated which showed that in the air freight cargo equation the world consumer price index estimated by OLS (-2.4909) was significant at the 10 percent significance level while previous year's world price index had a negative and significant short-run causal effect on air freight cargo's growth. In contrast to the previous year, the world consumer price index had a positive and significant short-run effect on the other airlines' passenger growth rates. The world consumer price index has positive and significant effect on other airlines' passenger demand growth while this world consumer price index has negative and significant short run effect on Ethiopian's air freight cargo. This implies passengers are not responsive to price change which might be due to absence of a close substitute for other airlines' transport. This results in an increase in aggregate demand. In the latter case airfreight cargo shipment is price sensitive to an increase in consumer price index. Hence, unlike the former the latter has sea freight shipment and land transport as an alternative that can relatively substitute air freight cargo. In both the equations (other airlines' and air freight cargo), the world consumer price index had no long-run causal effect.

Energy plays a major role in the transport industry. Hence, this study assumed energy to be the most important determinant factor for transport service provisions though its price directly impacted passengers negatively. This finding shows that world crude oil prices have a short-run (-8.54 percent) and long-run (41.14 percent) causal relationship with Ethiopian's passenger growth in the opposite direction (expected) and in the same direction (unexpected) respectively. In the growth determinants of other airlines, world crude oil prices in the current year (1.1811 percent) and previous year (-0.9839 percent) had short-run and long-run (1,0626 percent) causal relations. Similarly, in the air freight cargo growth model, previous year's world crude oil prices had a short-run (-0.6526 percent) causal relation as expected and also had a long-run (0.6479 percent) causal relation. This shows that other airlines' passengers and airfreight cargo will take time to respond and hence, only previous year's increase or reduction in world crude oil prices will have a negative effect while current year's prices will have a short-run as well as long-run effect thus playing a complementary role in the growth of other airlines' passenger and air freight transport. This may be due to continued growing aggregate demand for the air transport sector.

Another important factor that determines growth of the air transport sector is the currency exchange rate. It is obvious that people, goods, and services are transported across countries and exchange rate plays a significant role in this. This study found that the exchange rate had short-run (0.7571 percent) and long-run (-0.3966 percent) effects on the growth of Ethiopian's passengers while in the case of other airlines, any change in the exchange rate had long-run (0.3191 percent), short-run previous year (2.2683 percent), and current year (-2.2184 percent) effects on the growth in their passengers. In the air freight cargo segment, the exchange rate had a -1.4967 percent long-run and a 1.5169 percent previous year short-run effect on growth. In the long-run, the average exchange rate had a significant and expected impact on the growth of Ethiopian's passengers and air freight cargo while in the case of other airlines only the current year short-run effect was observed. Other estimation results such as long-run and short-run previous year in the other airlines' growth determinants, short-run growth determinants of Ethiopian and short-run previous year air freight growth showed positive and significant results. Other airlines' passengers were not responsive to a change in the average exchange rate while in the short-run Ethiopian's passenger and air freight cargo were not sensitive to a change in the exchange rate particularly during the current and previous years. In addition, increasing aggregate demand and absence of close substitutes, may not have directly impacted some air transport services by the exchange rate. The OLS and SUR models' estimations of the average exchange rate were statistically significant and as expected (-1.1252 percent) and (-1.1376 percent) respectively.

The variable used for explaining the effects on Ethiopian's air freight cargo is the total volume of imports and exports of goods and services. Ethiopia has experienced unbalanced trade for many years and this challenge is continuing. Despite this, air freight cargo is an important mode of transport. The study assumed total volume of imports and exports to have a positive and significant impact on the growth of air transport. The findings of the study show that in the short-run the volume of exports and imports (1.2170 percent) had a positive and significant causal relation with air freight cargo's growth while the OLS estimation (-0.5129 percent) as well as the long-run ARDL model's results (-0.9894 percent) were negative and significant. This means that due to extremely high volumes of national imported and exported goods, air freight cargo transport did not complement other transport modes and was instead a substitute. The reason for such a result is that airfreight is expensive as compared to other modes of transport and also has a limited capacity.

Following the determination and estimation of long-run coefficients of the three equations, the short-run VEC model which is a one lagged period residual obtained from the estimated dynamic short-run model, refers to the speed of adjustment to restore the equilibrium in the dynamic model after a shock. The coefficient of the error correction term for Ethiopian's passengers, other airlines' passengers and airfreight cargo growth determinants have the expected negative signs (-0.9904, -1.6786, and -1.3646) and are strongly significant. This suggests the existence of a high speed of adjustment to the equilibrium after a shock to all the air transport's growth determinants. Approximately 0.9904 percent, 1.6786 percent, and 1.3646 percent of the disequilibrium that comes from a one period lagged shock converges back to the long-run equilibrium in the current year. Such highly significant VEC provides evidence for the existence of a stable long-run relationship between air transport growth and the specified determinants' variables.

The major findings show that most variables were significant in the short-run and long-run and their respective VEC models were also significant and as expected showing that the study found a strong causal relationship among their respective explanatory variables in general. In some cases, specific explanatory variables had significant but with reverse signs which can be attributed to the heavy dependency on imported goods and services, no close substitute for passenger air transport, and growing aggregate demand for air transport.

The pairwise Granger causality test's results showed that national per capita income had a bi-directional causal relationship with Ethiopian's passenger growth and a unidirectional causal relationship with other airlines' passenger growth. Likewise, real GDP had a unidirectional causal relationship with air freight cargo. This means that economic growth had a significant impact on overall Ethiopian air transport growth in the short-run and long-run specifically for other airlines' passenger and airfreight cargo growth while the effect was not significant in effecting the economic activities in the reverse direction due to the limited number of passengers and air freight cargo as compared to Ethiopian's passenger growth and total volume of imports and exports through other modes of transport respectively. The bi-directional causal relationship of per capita income and Ethiopian's passenger growth implies that in the long-run the dominant Ethiopian passenger growth will play a significant role in increasing economic activities in the country. Similarly, in the long-run economic growth in the country will significantly impact air transport growth.

Ethiopian is playing a significant role in transporting and connecting people, goods, and services with the world. Hence, the government should support Ethiopian for its globally competitive provision of passenger and airfreight services; the limited airfreight cargo volumes as compared to other modes of transport should be improved by motivating domestic investors to export using airfreight cargo, and increasing cargo flights to other destinations based on demand. In addition, the heavy dependency on imports and exchange rate shortages should be improved through export-led industrialization. Since growth of air transport depends on the overall growth of the economy, structural changes should be speeded up for a transition from an agrarian economic structure to industrialization. This entails increasing demand for air transport. Attention needs to be paid to policies oriented towards growing and expanding domestic industrial output, standardizing and improving the quality of products that can further assist the trade balance and reduced dependency and instability of the world crude oil prices, the world consumer price index and exchange rate volatilities.

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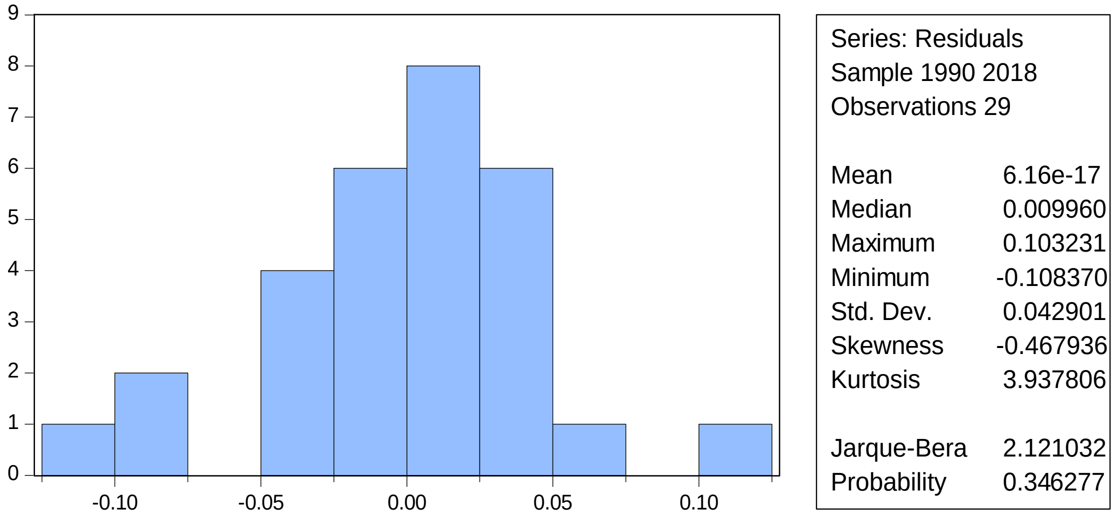
Appendix A4

Table A4.1: Phillips-Perron (PP) unit root test's results

Variable	At level		First difference		Order of Integration
	Intercept (p-value)	Intercept and Trend (p-value)	Intercept (p-value)	Intercept and Trend (p-value)	
lnYe	1.0000	0.5692	0.0000	0.0000	I(1)
lnYo	0.6540	0.0188	0.0000	0.0000	I(0)
lnYc	0.9702	0.5664	0.0001	0.0001	I(1)
Lnetap	0.6496	0.5907	0.0056	0.0251	I(1)
lnindoutput	0.5713	0.7769	0.0067	0.0176	I(1)
Lntourist	0.9965	0.5844	0.0004	0.0014	I(1)
Lnrgdp	0.9999	0.5835	0.0000	0.0000	I(1)
Lnpcim	0.9997	0.8921	0.0400	0.0448	I(1)
Lnwcpi	0.9401	0.5907	0.0017	0.0091	I(1)
Lnwoilpb	0.4684	0.5785	0.0001	0.0000	I(1)
Lnxem	0.9406	0.7004	0.0177	0.0689	I(1)
Lnaxcr	0.7962	0.6084	0.0702	0.2469	I(1)

Figure A4.1: Parameter stability tests, Ethiopian's passengers

a. Jarque-Bera



b. CUSUM of Squares of residuals

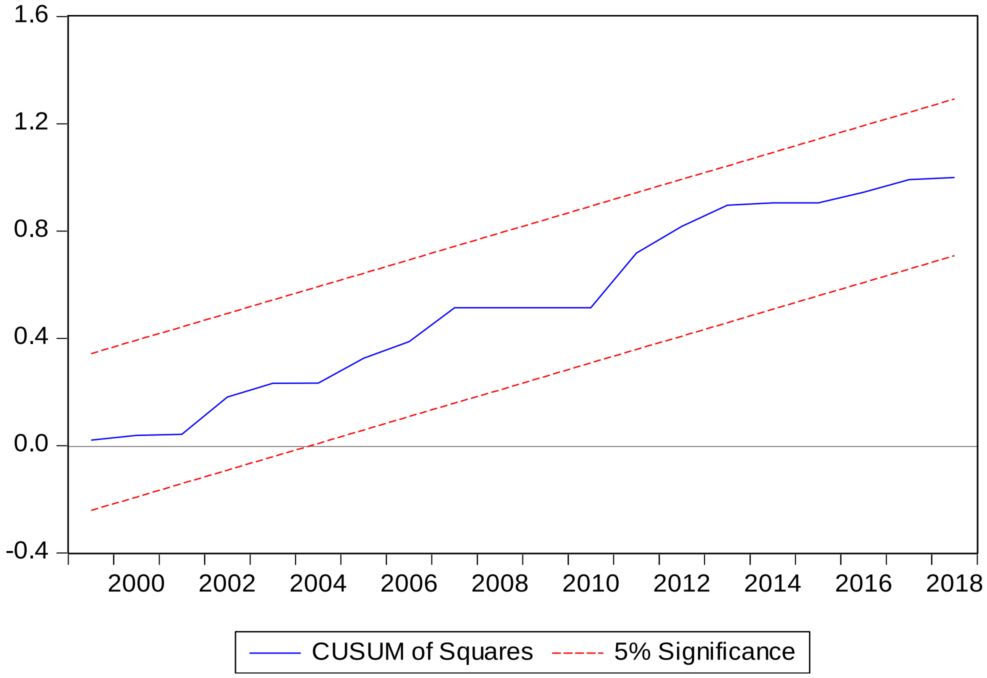
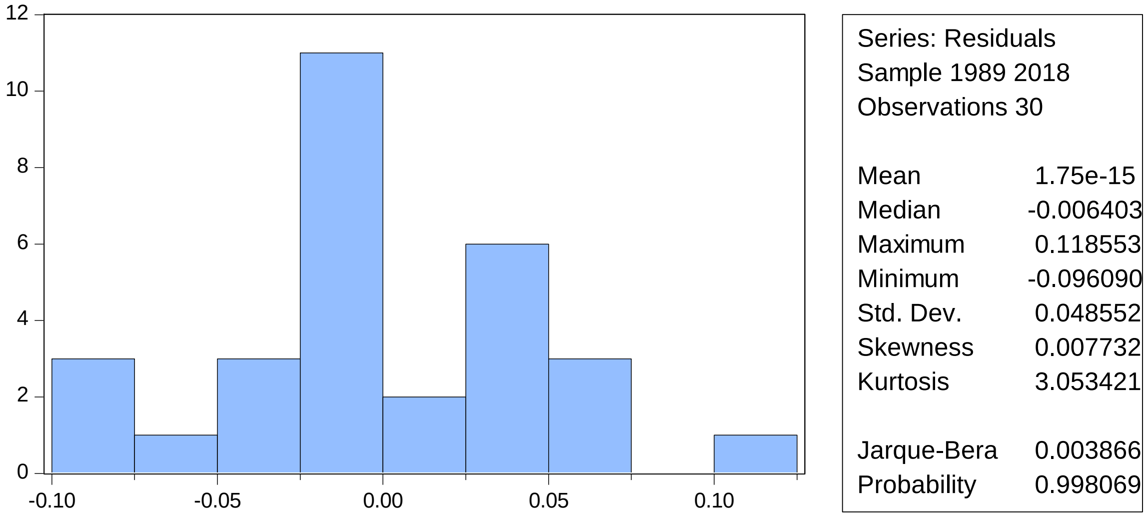


Figure A4.2: Parameter stability tests, other airlines' passengers

a. Jarque-Bera



a. CUSUM of Squares of residuals

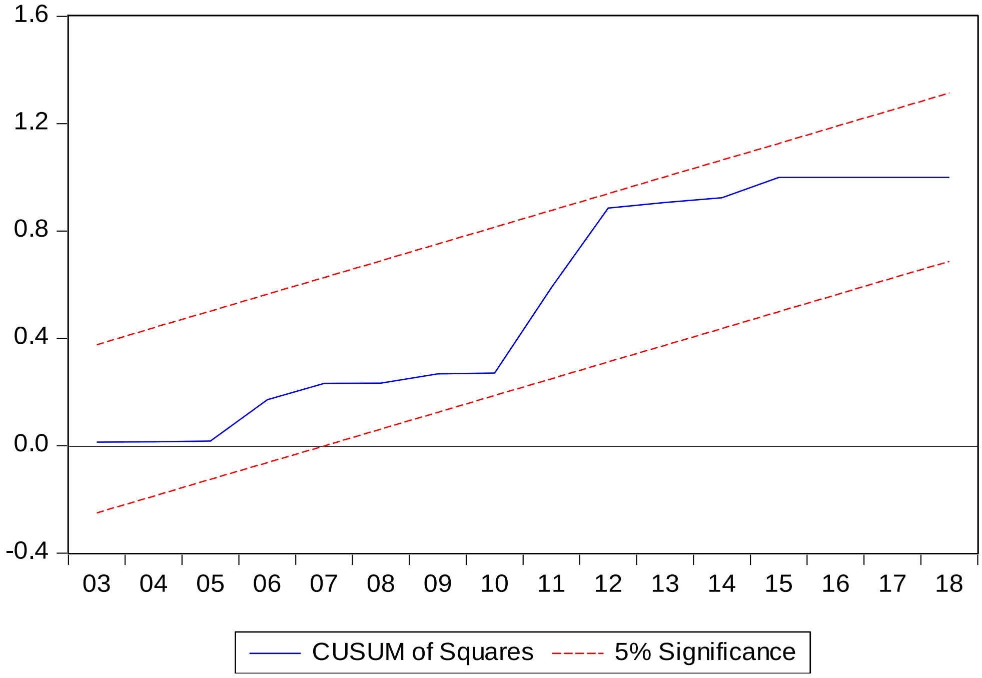
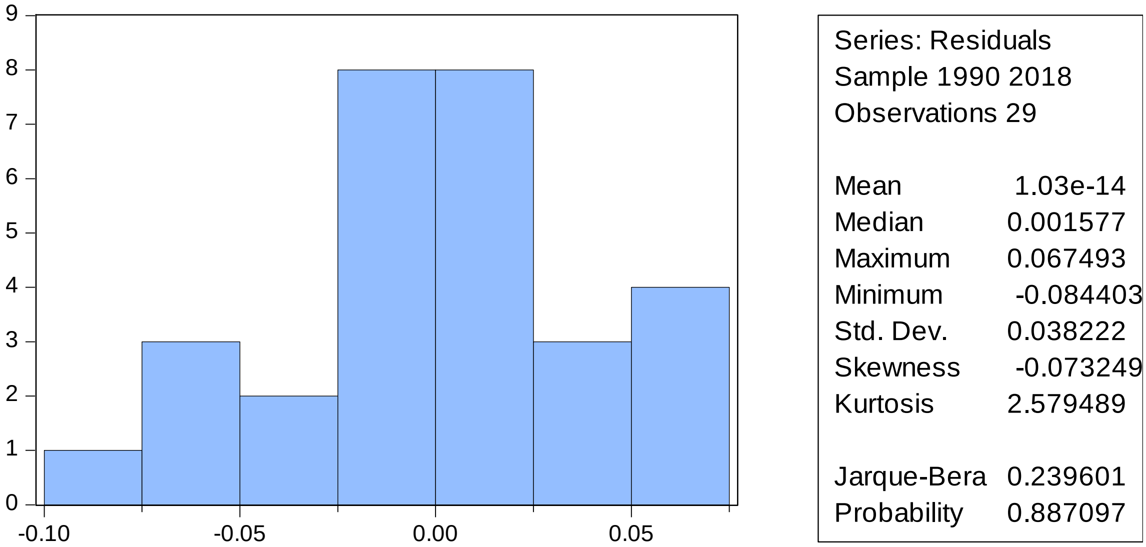


Figure A4.3: Parameter stability tests, air freight cargo

a. Jarque-Bera



b. CUSUM of Squares of residuals