Productivity and Efficiency of Farm Households and Urban Poverty Dynamics in Ethiopia

OUMER BERISSO

A Dissertation Submitted

to

The Department of Economics

Presented in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

Addis Ababa University

Addis Ababa, Ethiopia

February 2018

Addis Ababa University

School of Graduate Studies

This is to certify that the dissertation prepared by **OUMER BERISSO** titled: "**Productivity and Efficiency of Farm Households and Urban Poverty Dynamics in Ethiopia"** and submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy (Economics) complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

Signed by the examining Committee:

External examiner:

Prof. Salvatore Di Falco Signature: ________ Date: 01 February 2018

Internal examiner:

Dr. Bamlaku Alamirew Signature: ________ Date: 01 February 2018

Main (chair) Supervisor:

Prof. Almas Heshmati (JIBS) Signature: ________ Date: 01 February 2018

Co-supervisors:

Prof. Pär Sjölander (JIBS) Signature: ________ Date: 01 February 2018

Assoc. Prof. Alemu Mekonnen (AAU) Signature: _________ Date: 01 February 2018

____

Chair of Department or Graduate Program Coordinator

Addis Ababa University
School of Graduate Studies

This is to certify that the dissertation prepared by Oumer Berisso entitled: "*Productivity and Efficiency of Farm Households and Urban Poverty Dynamics in Ethiopia*" and submitted in fulfillment of the requirements for the Degree of Doctor of Philosophy (Economics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the examining Committee:

Examiner	Prof. Salvatore Di Falco	signature	Date 1/2/2018
Examiner	Dr. Bamlak Alamirew	signature	Date 01/02/18
Advisor	Prof. Almas Heshmati	signature	Date 2018-02-01
Advisor	Prof. Par Sjolander	signature	Date 20180201
Advisor	Dr. Alemu Mekonnen	signature	Date 1/2/2018

Chair of Department or Graduate Program Coordinator

DECLARATION

I, **OUMER BERISSO,** hereby declare that this thesis entitled "**Productivity and Efficiency of Farm Households and Urban Poverty Dynamics in Ethiopia"** is the product of my original research work. It is a dissertation that has been submitted to the Department of Economics, Addis Ababa University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics. I solemnly declare that I have undertaken the research work independently with the guidance and support of my supervisors and that all sources of materials used for this thesis have been duly acknowledged. I declare that this thesis is not submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate. This work has also accredited the views of the research participants. The reporting procedures do comply with the expected standards and regulations of the university.

Name: **OUMER BERISSO METAKSA**

Signature:

Place: Department of Economics,

College of Business and Economics,

Addis Ababa University

February 2018

To:

My parents, *Hajite* **HAWI JIBICHO** and *Haji* **BERISSO METAKSA**

May Allah rest their gentle and loving soul in Heaven!

ACKNOWLEDGEMENTS

First and foremost, I owe it all to Almighty Allah for granting me all the competence, wisdom and health to reach this level. Completion of this doctoral dissertation is the product of contributions from several individuals and institutions. Many people have encouraged and supported me professionally, materially, and morally throughout my PhD study. They all deserve my sincere appreciation. I am grateful to all of those who, in one way or another, have played a part in the successful completion of this thesis.

Above all, I am very grateful to my Principal Supervisor Professor Almas Heshmati, for his relentless, sympathetic and continuous support during my long doctoral research journey. His scientific guidance and encouragement right from the beginning to the completion of the thesis is commendable. His critical comments, though look painful at times, are constructive and worthy in the end. I am indeed indebted to him for his infallible advice on both academic issues and those related to my personal life. I particularly remain indebted for his understanding and real support during my hard times, especially when I was really dejected and depressed on the occasion of my mother's decease. Thank you very much, dear Professor Almas, for all your support and kindness.

I would like to also express my sincere gratitude to my co-supervisor, Professor Pär Sjölander, for his compassion, enthusiasm and his comments and suggestions at each stage of the research. His modest approach and constructive comments are wonderful and encouraging. Prof. Pär, your contributions in econometric and statistical analysis have helped me a lot throughout the research process and writing of the thesis.

I gratefully acknowledge my Ethiopian co-supervisor, Associate Professor Alemu Mekonnen (PhD), for his guidance, continuous encouragement, and insightful comments. He often went beyond his advisory duty, being always available by phone, and even calling me with his own personal phone whenever he had something important for me. Especially, I am indebted to Dr. Alemu for his unfailing support and assistance in soliciting funds for my PhD thesis project.

My sincere appreciation also goes to the external reviewer of my thesis, Professor Giannis Karagiannis, Editor of European Review of Agricultural Economics and Associate Editor of the Journal of Productivity Analysis, for his valuable comments and suggestions that enabled me to improve the earlier versions of the manuscript. I would also like to take this opportunity to thank my professors who offered me courses both at the Department of Economics, Jonkoping International Business School (JIBS), University of Jönköping (JU), Sweden; and at the Department of Economics, Addis Ababa University, Ethiopia during my PhD course work. I also extend my sincere appreciation to Mr. Lars, Ms. Monica and Ms. Vaida at JIBS-JU, Sweden, for their administrative support and creating a good working environment at JIBS-JU.

I owe appreciation to my fellow former and current PhD students in the Department of Economics at Addis Ababa University: Dr. Atilaw, Dr. Atinaafu, Dr. Hailu, Dr. Mekonen, Getu, Kahsay, and Fantahun, for the wonderful time we had together on social and academic occasions and for all the fun we have had at every moments during our stay in JIBS, Sweden. I must extend my many thanks also to Mr. Kebede Bekele, post graduate coordinator of the Department of Economics, for his marvelous coordination and hospitality.

I gratefully acknowledge JIBS-JU, Sweden, under the auspices of SIDA, for its provision of every logistics: strengthening the program by providing supervisors, extending invitations to Sweden following up the progress of the dissertation, covering all providing access to the Internet and a comfortable office during all my visits to JIBS. The Environment for Development Initiative of the Department of Economics, University of Gothenburg, is also gratefully acknowledged for financing my PhD thesis project.

My special thanks and sincere appreciation goes to Dr. Jeylan and Dr. Kasim, for their relentless, continuous support and encouragement during my PhD study. You have cherished with me every great moment and supported me whenever I needed it. I owe you all a profound appreciation also for your useful personal advices and friendly encouragement at moments of my discomfort.

Words cannot express the feelings I have for my parents, my mother Hawi Jibicho and my father Berisso Metaksa, for their commitments to send me to school and for showing me the road of success. They deserve special thanks for their limitless love, encouragement and help at every stage of my personal and academic life. Their unwavering support for education, despite living their entire life in an illiterate society, was incredible. I am unlucky for missing them at this special moment in my life. May Allah rest their gentle and loving soul in Heaven!

My sincere appreciation also goes to my siblings, Abdulqadir, Hassan, Abdala, Jeylan, Qorsa, Makida and Abdurahaman, for all the necessary support and encouragement you provided me during my PhD study and for your follow-up in every stage of my academic career. I owe also my special gratitude to my uncles Hussen and Hassan for their continuous support and encouragement. My friends Dr. Jama, Dr. Kassaye, Tamam, Baca, Huseen, Hassen, Godi, Haji deserve special thanks for encouraging me and my family while I was on my study leave.

Finally, I must thank my beloved family, who are always the real source of my physical and mental strength. Most importantly, I owe my every success to my spouse, Munira Muhammad, who has stood by my side at all times, best and worst, and supported me in every possible way to see the successful completion of this work. Her total devotion and determination to take care of our children while I was abroad and to manage every family and social responsibility has encouraged me to focus on my research undertakings. My lovely kids, Ibsa, Hawi, Sonaan, and Ayantu, you are all the greatest source of my achievement, inspiration and wisdom. The time and attention I had for you during my study was too short. I feel your pain of missing full parental care at this early stage of your life. Congratulations! I am now back and fully available to give you the love of a darling father.

OUMER BERISSO
February 2018

TABLE OF CONTENTS

Contents **Page**

Chapter Five: Analysis of Factors Affecting Persistent and Transient Inefficiency of Ethiopia's Smallholder Cereal Farming

LIST OF TABLES

LIST OF FIGURES

Figures **Page**

Acronyms and Abbreviations

AESZ	Agro Ecological Sub Zone
AEZ	Agro Ecological Zone
AfDB	African Development Bank
AgSS	Agricultural Sample Survey
ATEM	Annual Maximum Temperature
CDPF	Cobb Douglas Production Function
CSA	Central Statistical Agency
CZ	Climatic Zones
CBN	Cost of Basic Needs
FEI	Food Energy Intake
DC	Developing Countries
DEA	Data Envelopment Analysis
DGP	Data Generating Process
DMU	Decision Making Unit
DTR	Diurnal Temperature Range
EAC	East African Countries
EEA	Ethiopian Economics Association
EfD	Environment for Development
ERHS	Ethiopian Rural Household Survey
ETB	Ethiopian Birr
EUHS	Ethiopian Urban Households Survey
FA	Farmers Association
FAO	Food and Agriculture Organization
FDRE	Federal Democratic Republic of Ethiopia
FEM	Fixed Effects Model
FGT	Foster Greer Thorbecke
FHH	Female Headed Households
GLS	Generalized Least Squares
GTFE	Generalized True Fixed Effects
GTP	Growth and Transformation Plan
HDI	Human Development Index
HH	Household
ICRISAT	International Crops Research Institute for the Semiarid Tropics
IFPRI	International Food Policy Research Institute
IIA	Independence of Irrelevant Alternatives
IPCC	Intergovernmental Panel on Climate Change
IWMI	International Water Management Institute
JLMS	Jondrow, Lovell, Materov and Schmidt
KH model	Kumbhakar and Heshmati Model
KLH model	Kumbhakar, Lien and Hardaker Model
LDC	Least Developed Countries
LR	Likelihood Ratio
LSDV	Least Squares Dummy Variable

MDG	Millennium Development Goals
MDU	Man Day Units
ME	Marginal Effects
MEDaC	Ministry of Economic Development and Cooperation
MHH	Male Headed Households
MLE	Maximum Likelihood Estimate
MMT	Monthly Mean Temperature
MNL	Multinomial Logit
MoA	Ministry of Agriculture
MoFED	Ministry of Finance and Economic Development
MPI	Multidimensional Poverty Index
NMA	National Meteorological Agency
NPC	National Planning Commission
OLS	Ordinary Least Squares
OPHDI	Oxford Poverty and Human Development Initiative
OTE	Overall Technical Efficiency
PCCE	Per Capita Consumption Expenditure
PFP	Partial Factor Productivity
PGI	Poverty Gap Index
PHCI	Poverty Head Count Index
POLS	Pooled Ordinary Least Squares
PRECIP	Precipitation
PTE	Persistent Technical Efficiency
QR	Quantile Regression
RE	Random Effects
RTE	Residual Technical Efficiency
RTS	Returns to Scale
SD	Standard Deviation
SE	Standard Error
SFA	Stochastic Frontier Analysis
SPGI	Squared Poverty Gap Index
SSA	Sub Saharan Africa
TC	Technical Change
TE	Technical Efficiency
TFEM	True Fixed Effect model
TFP	Total Factor Productivity
TLPF	Translog Production Function
TLU	Tropical Livestock Unit
TTE	Transient Technical Efficiency
VIF	Variance Inflation Factor

Outline of the Dissertation

This thesis analyzes productivity and efficiency of farm households and urban poverty dynamics in Ethiopia using household level panel datasets. The dissertation is organized into five chapters. The first chapter (the introductory chapter) provides introduction and summary of the dissertation. It presents the general background information on global climate change and agriculture, the Ethiopian economy, the agricultural sector, and the status of poverty in the country. It gives a brief theoretical and empirical literature review on climate change, productivity and efficiency. It also presents statement of the problem, objectives of the dissertation, and methodological approaches and the datasets used in the thesis. Further, the introductory chapter provides a summary of the research and highlights its contributions and policy implications. Chapters 2-5 present four self-contained and inter-related essays; they consist of pieces of research to make up a PhD thesis in the field of applied economic analysis. The earlier versions of each essay were presented at national and international conferences and seminars. Earlier versions of the first two essays have been already published as chapters in two edited books (Heshmati, 2016, 2017) while the third essay appeared in a working paper.

Among the four essays, the first essay (chapter 2) examines determinants of consumption expenditure and poverty dynamics in urban Ethiopia over the period 1994-2009. An earlier version of this chapter was presented at the 1st Annual Eastern African Business and Economics Watch (EABEW), an international conference organized in Kigali, Rwanda in May 2015, by Jönköping International Business School (JIBS), University of Jönköping (JU), Sweden, in collaboration with the University of Rwanda, College of Business and Economics (UR-CBE).The chapter was also presented at the National Conference on Population and Development, organized by Mekelle University, Ethiopia, in August 2015. Moreover, its revised version was published as a book chapter in Heshmati, (ed.) (2016), Poverty and Well-Being in East Africa: A Multi-faceted Economic Approach. Switzerland: Springer, ch. 7, 139-164.

The other three essays focus on measuring and explaining production efficiency of cereal producers using a stochastic production frontier analysis. The second essay (chapter 3) specifically focuses on analyzing the effects of weather variations on cereal productivity and influence of agro-ecological differences in Ethiopian cereal production, while the other two essays (chapters 4 and 5) focus on distinguishing farm heterogeneity from persistent and transient efficiency components and explaining the effects of socioeconomic and demographic determinant factors and the forces behind persistent and transient efficiency differentials across cereal producers respectively.

Chapter three assesses the influence of weather variations and agro-ecological differences on cereal productivity. An earlier version of this chapter was presented at the 2nd EABEW International Conference, organized in Kigali, Rwanda in June 2016, by JIBS-JU, Sweden, in collaboration with UR-CBE. Further, its modified version appeared in East Africa Research Papers in Economics and Finance (EARP-EF), working paper No. 2016:07, and it was published as a book chapter, in Heshmati, (ed.) (2017), Economic Transformation for Poverty Reduction in Africa, UK, London, Routledge,ch.2, 9-35.

Chapter four presents an essay that investigates farm-heterogeneity and persistent and transient productive efficiencies in Ethiopia's smallholder cereal farming. An earlier version of this chapter was presented at the 5th Annual Conference on the Eastern Ethiopia Economic Development, co-organized by Haramaya University and the Ethiopian Economics Association Eastern Chapter, in Dire Dawa, Ethiopia, in December 2015. It was also presented in a seminar organized by the JIBS-JU, Sweden, in January 2016, and a revised version of the chapter appeared in East Africa Research Papers in Economics and Finance (EARP-EF), working paper No. 2017:16.

The final chapter (chapter 5) presents an essay that explains factors affecting persistent and transient inefficiency of Ethiopia's smallholder cereal farming. An earlier version of the chapter was presented in a seminar organized by JIBS-JU, Sweden, in February 2017. Further, its revised version was also presented at an international conference, organized by JIBS-JU, Sweden, in collaboration with Addis Ababa University, College of Business and Economics, December 7-8, 2017 in Addis Ababa, Ethiopia and also at the 1st International Conference, organized by Arsi University, December 15-16, 2017 in Asella, Ethiopia.

CHAPTER ONE: Introduction and Summary of the Thesis

1.1 General Background of the Study

1.1.1 Global Climate Change and Agriculture

Global climate change and its associated extreme incidences continue to pose considerable challenges in various forms. As per the Intergovernmental Panel on Climate Change (IPCC, 2014), the earth's surface global mean temperature increased substantially over the 20th century and projections suggest a continuous increase in global temperatures. IPCC predicts an increase in temperatures by about 1 to 3°C by mid-21st century and by about 2 to 5°C by the end of the 21st century. This increase will depend on the emission scenarios and their realizations. Along with temperature increase, global warming is also associated with changes in large-scale hydrological cycles. Such global warming will alter the natural climate and environmental systems leading to increased frequency of extreme weather events, shifting precipitation patterns and changes in its intensity (Umesh et al., 2015). As a result, climate change is becoming a major threat for life on our planet.

Climate change induced variations are also assumed to have significant social, economic and environmental impact in the form of making water resources scarce, impacting agricultural production and food systems, forced migration and poverty incidences (Umesh et al., 2015). The impact of existing and predicted climate changes varies across economies. Those with large dependence on climate sensitive sectors such as agriculture are likely to be the most affected. Given the agricultural sector's contribution to livelihoods, production and employment the economic cost of climate change induced variations in such countries is high. Moreover, poor countries can incur huge costs from a small deviation in temperature, particularly due to their poor adaptive capacity, lack of necessary technology and lack of resources to deal with climate change (Beyan et al., 2013).

Several scientific studies have suggested that developing countries (DCs) in particular are suffering from the burden of the ever-changing climatic conditions. These have induced food shortages and chronic diseases and poverty among billions of people (IPCC, 2014). African countries are more vulnerable to climate change because of additional temperature increases due to warming that would affect their marginal water balance and harm their agricultural sector and their dependence on rain-fed agriculture, lead to high levels of poverty, low levels of human and physical capital and poor development infrastructure (Chauvin et al. 2012). Sub-Saharan Africa (SSA), in particular, has been identified as one of the parts of the world that are the most vulnerable to the negative impact of climate change as they possess minimum financial and technical resources to cope with it (IPCC, 2014). According to IPCC, by 2050 average temperatures in Africa are predicted to increase by 1.5 to 3°C, and will continue to move upwards beyond this time. Warming is very likely to be larger than the global annual mean warming throughout the continent and in all seasons. Climate change directly affects agricultural production as agriculture is inherently sensitive to climate/weather conditions making it one of the most vulnerable sectors to the risks and impacts of global climate change (IPCC, 2012).

Agricultural production is the main source of livelihood and employment for most rural inhabitants in SSA and East African countries (EAC). Despite being a large sector in national economies, agricultural production systems in SSA are largely rain-fed and thus their success is sensitive to climate change and its variability. In addition, rapidly growing populations in the region have further increased pressure on food production systems. The negative effects of climate change on agricultural crop production are particularly pronounced in EAC as the sector accounts for a large share of GDP, export earnings and employment in most countries. In the region the agricultural sector employs 65 per cent of the labor force and contributes 32 per cent to the countries' national GDP. However, it is characterized by low productivity and lack of modern farming technologies (Chauvin et al., 2012). In the East African region, and the Horn in particular, hydro-meteorological disasters especially droughts and floods are the most common forms of natural disasters. They account for 80 per cent of loss of life and 70 per cent of the economic losses related to hazards (Umesh et al., 2015).

1.1.2 The Ethiopian Economy and Agriculture

Ethiopia is a densely populated agrarian economy in Africa. With a fast-growing population (2.45 per cent per year), Ethiopia is the second most populous country in SSA. Its current population of 104.4 million is predicted to double in the next 30 years provided the growth continues at the same rate (the World Bank, 2017). This rapid population growth is putting pressure on land resources and increasing environmental degradation and vulnerability to food shortages. The country has achieved creditable developmental results over the past decade as its economy grew at an average of 10.8 per cent per year in 2004-15 (NPC, 2016; the World Bank, 2017). Agriculture is an important economic activity in Ethiopia. It plays a key role in economic growth, poverty reduction, food security and employment. The sector, contributing the largest share to the national GDP, provides employment and livelihood to more than 80 per cent of the country's population. It contributes 81 per cent to the country’s total export earnings and is the primary source of food providing up to 85 per cent of the country’s food supplies (AfDB, 2016). On average, agriculture grew by 6.6 per cent during the country’s first Growth and Transformation Plan (GTP I, 2010/11-2014/15) while its share in GDP averaged 41.5 percent in 2010; this consistently declined during the period reaching 38.5 per cent by 2015 (NPC, 2016).

Ethiopia’s economy and agro-ecological system are fragile and as such vulnerable to climate change. This is reflected in low levels of productivity and incomes and high vulnerability to rainfall variations and changes. The country is experiencing an increase in temperature and declining rainfall patterns as well as increased frequency of extreme climate events (such as droughts and floods) as a result of climate change. According to Belliethathan et al., (2009) the mean temperature in Ethiopia is predicted to increase by 0.9 to 1.1^{o}C by 2030, by 1.7 to 2.1^{o}C by 2050 and by 2.7 to 3.4^{o}C by 2080. Climate/weather effects in Ethiopia are associated with negative changes in precipitation patterns, rainfall and temperature variability which could increase the country's frequency of droughts and floods. A decrease in seasonal rainfall in particular has devastating implications for agricultural production leading to food insecurity, malnutrition and famine (Nhemachena and Hassan, 2007).

Seven to 8 per cent of Ethiopia's economy is affected by climate change (UNDP, 2015). Further, the country annually loses 2 to 6 per cent of its total agricultural production due to climate change (MoFED, 2010). The economy's vulnerability to climate change, combined with plans of achieving accelerated and green growth demand that the Government of Ethiopia make significant investments every year for mitigating climate change and adapting to it (UNDP, 2015). Ethiopia has huge agricultural potential due to its ample arable land, an abundant workforce and diverse agro-ecological zones such as highland (Dega), midland (Weyna-Dega) and lowland (Kolla). However, the country's agriculture remains highly vulnerable to weather variability (both in terms of seasonal variations and annual fluctuations in precipitation) and frequent droughts (Beyan et al., 2013; FAO, 2016). The sector is characterized by traditional technologies and is dominated by smallholders who contribute/produce more than 90 per cent of the total crop output and cultivate more than 95 per cent of the crop land.

However, despite its crucial role, achieving productivity gains in the agriculture sector has been an important challenge for Ethiopia as the sector is characterized by low productivity and production inefficiencies. Various factors contribute to this state some of which are attributable to high dependency on traditional practices, rain-fed farming on small and highly fragmented farmlands, high population pressure, severe environmental degradation and frequent droughts (Tsegaye and Berg, 2010); low use of improved inputs and modern technologies, weather instability, pests and diseases (Birhanu and Zeller, 2011); and inadequate access to well-functioning markets, limited access to credit and inefficient utilization of scarce resources (Bezabih et al., (2014a, 2014b); MoFED, 2010 and NPC, 2016).

The performance of major crops has been a major contributor to overall growth in agriculture and allied activities (MoFED, 2010; NPC, 2016). Major agriculture and rural transformation targets of GTP II are increasing crop and livestock production and productivity, promoting natural resource conservation and utilization and ensuring food security. The plan intends to boost agricultural production by solving the problems of input supply and technology adoption. It hopes to achieve this goal by focusing on smallholders and allowing the sector to play a role in stabilizing the economy and supporting a transition to agro-based light manufacturing and agro-allied industrial growth in general (NPC, 2016).

Cereals are the most vital and major crop in Ethiopia's grain production; Ethiopia is the largest cereal producer in Africa. Different cereals are grown in different geographic areas. The primary cereals grown in Ethiopia are teff, maize, sorghum, barley, wheat and millet. Cereals comprise about two-third of the agriculture sector's share of GDP and close to one-third of the national

GDP (CSA, 2014). Thus, cereals have a lion's share in the country's crop farming in terms of production volumes and farmland and farm households' incomes. According to CSA (2014) cereals comprised about 79 per cent of the total cropped area and 85 per cent of grain crop production and engaged 81 per cent of private farmers for the Meher cropping season (the main season) in the 2013-14 production year. CSA's yearly reports show that cereal production was marked by remarkable growth in Ethiopian crop farming during 2004-14. Cereal production consistently grew from an average of 16 million metric tons (MMTs) in 2004-08 to 21.6MMTs during 2009-14. This shows that cereal production on average was 18.8 MMTs with a growth rate of 2.74 per cent per annum for the decade 2004 to 2014. Accordingly, cereal productivity increased from 15.7 quintal per hectare in 2009-10 to 21.5 quintal per hectare by the end of 2014-15. NPC (2016) notes that; the major factors for the shortfall in major crop (cereal) productivity are related to the coverage and quality of implementation of the agricultural extension system and low supply of improved inputs. For example, the amount of fertilizers and improved seeds supplied accounted only for about 72 and 42 per cent of the target set during the GTP I period (NPC, 2016).

According to existing studies, productive sectors like the agricultural sector in the Ethiopian economy are currently operating below their potential production capacity as the factors of production are not efficiently utilized in the production process (NPC, 2016). Moreover, it has also been noticed that the economy's technical efficiency and technological progress is at a low level. It was to reach the production possibility frontier of the economy from this low level that the Ethiopian government came up with GTP II. The plan aims to enhance efficient utilization of resources with a sense of urgency (NPC, 2016). Its other priority areas include transforming the agricultural sector to an efficient sector and enhancing the productivity of smallholder farms which are the main source of growth in the sector. In its GTP II document the government states that productivity enhancement in the agricultural sector is only possible through proper management and dissemination of available technologies; implementing or scaling up best practices for model smallholder farmers; and tackling the challenges which have constrained the achievement of farmers' efficiency potential. Hence, for Ethiopia as an agriculturally dependent country with a food deficit gap (the World Bank, 2017; UNDP, 2015) increasing production and enhancing farming efficiency is not a matter of choice but is instead a must.

1.1.3 Poverty and its Dynamics in Ethiopia

Despite its recent growth performance, Ethiopia remains one of the least developed countries in terms of standard development measures including poverty levels (MoFED, 2013 and UNDP, 2014). Poverty still remains relatively high in the country due both to rapid population growth and a low starting base. Almost a third of Ethiopia's 104 million people still live below the poverty line (the national poverty line) and food insecurity remains a major challenge (the World Bank, 2017). With 29.6 per cent of the population living below the national poverty line Ethiopia ranks the 41th poorest countries or 146 out of 187 countries in the world. Nevertheless, its economic growth performance has brought markedly commendable development results over the past decade. One of the achievements is a positive trend in poverty reduction in both urban and rural areas.

Consequently, the country's extreme poverty which was 55.3 per cent in 2000 reduced to 33.5 per cent in 2011 (as measured by the international poverty line of less than $1.90 per day). The country's poverty level as measured by consumption expenditure shows that the poverty rate was 45.5 per cent in 1995 which declined to 38.7 per cent in 2004-05 and fell gradually to 29.6 per cent in 2010 (MOFED, 2010). This is estimated to have further declined to 23.4 per cent in the country's second plan (NPC, 2016). This result is attributed to agricultural growth which was the main driver in poverty reduction augmented by large-scale pro-poor public spending on basic services such as the safety net program which too contributed to reducing poverty. The country also achieved considerable progress (AfDB, 2016) in other development indicators such as human development measures. The country's HDI increased significantly over the past decade from 0.284 in 2000 to 0.429 in 2012 and 0.435 in 2013 (HDR, 2014) showing an annual increase of about 3.34 per cent. However, in addition to its high poverty levels, Ethiopia remains one of the most inequitable countries in the world with very low human development indicators; it is ranked 174 out of 188 countries with a Gini-coefficient of about 0.30 (AfDB, 2016).

Despite urbanization growing at a fast rate, Ethiopia is categorized as one of the least urbanized countries in the world. The country's urban habitats are estimated to be only 20.3 per cent of the population, which is below the SSA's average of 37 per cent (the World Bank, 2017). Nevertheless, the urban population has been growing at an average 3.8 per cent per annum since 2005; this moved to 4.3 per cent in 2006, 3.57 per cent during 2010-13 and 4.89 per cent in 2015 while the country's population grew at 2.45 per cent in 2017.

Various organizations have made projections about Ethiopia's (urban) population growth including the national CSA (2007) which projected that the 12 million urban population in its official census will grow to 15.2 million in 2012, 17.8 million by 2015 and 22 million by 2020. Meanwhile, the Oxford Poverty and Human Development Initiative **(**OPHDI) projected the urban population to be about 21.2 million in 2017 or 20 per cent of the current population which is expected to triple to 42.3 million by 2037 (OPHDI, 2017). If not addressed this could pose a significant development challenge. As per the United Nations World Population Review (2017), Ethiopia has one city with more than a million people, nine cities with between 100,000 and 1 million people, and 83 cities with between 10,000 and 100,000 people. Addis Ababa, the largest city (capital) in Ethiopia has an estimated population of 3.6 million in the city proper. Combined with the population in the metro areas this figure reaches more than 4.6 million (UNWPR, 2017). Other cities such as Adama (324,000), Gondar (323,900), Mek'ele (323,700), Hawassa (300,100), Dire Dawa (277,000), Bahir Dar (243,000), Dese (187,900) and Jimma (177,900) are among the major cities/towns with the highest habitats in the country (UNWPR, 2017).

As a developing country both rural and urban poverty are important in Ethiopia. However, poverty levels and the proportion and pace of its reduction differ in rural to urban areas. Between

1995 and 2005 poverty declined in rural areas from 47 to 39 per cent while it increased in urban areas from 33 to 35 per cent. In 2010, the proportion of the population below the poverty line stood at 30.4 per cent in rural areas while it was 25.7 per cent in urban areas (AfDB, 2016). The main reason for the higher incidence of poverty in rural areas is low agricultural sector productivity. Policymakers need to recognize rapid urbanization as both an opportunity and a challenge. As an opportunity it promotes a dynamic self-sustaining urbanization process which is an integral part of the country's economic structural transformation. According to AfDB (2016) although urban centers comprised 20 per cent of the population, they contributed 38 per cent to the country's GDP, signaling the vital role that urbanization plays in diversifying an economy. Further, it noted that towns and cities accommodated 60 per cent of all new jobs created in the country between 2005 and 2011. However, rapid urbanization also poses a big challenge as it demands attention and investments for establishing basic infrastructure like health, education, housing, roads, water and sewerage and recreational facilities.

Policies that encourage further agglomeration through urbanization will help in increasing poverty reduction. This in turn will require policies that favor the entry and growth of firms in addition to providing support to self-employment in non-agricultural activities through appropriately designed urban development projects. Programs targeted at improving the well-being of the urban poor will also become increasingly important. Recent official estimates show that poverty levels have declined sharply in rural areas. In contrast, there has been an increase in urban poverty although at a decreasing rate. OPHDI (2017) estimates that; 20 to 33.3 per cent of the Ethiopian population is vulnerable to poverty (23.5 per cent urban and 3.2 per cent rural population). Hence, urban growth has been combined with a high prevalence of urban poverty. According to some studies there is a growing trend in urban poor in the country. While sustained growth is central to development in countries like Ethiopia, the possibility that poverty spells caused by short-lived shocks may persist are a matter of concern.

This situation requires enhancing rural-urban linkages. Linking rural agricultural producers to urban markets through physical, economic, social and political connections is crucial. Strong linkages between agricultural producers, particularly smallholders and urban consumers can propel economic development and improve food security and nutrition for both rural and urban areas. Cities create opportunities for well-linked rural producers who can supply urban areas with nutritious food benefiting from larger, urban markets at the same time. These producers in turn can invest in creating rural agricultural and non-agricultural economic opportunities. In many developing countries these vital linkages are already improving (IFPRI, 2017).

1.2 Literature on Climate Change, Productivity and Efficiency

1.2.1 The Nexus between Climate/Weather Variations and Crop Production

Agricultural crop production is highly dependent on weather and climate for producing the food and fiber necessary for sustaining human life. Not surprisingly, crop production is deemed to be an economic activity that is vulnerable to weather and climate variabilities and changes. It involves natural processes that frequently require fixed proportions of nutrients, temperatures, precipitation and other conditions (Vuren et al., 2009, in Yohannes, 2016). Climate change affects crop production in a number of ways including through changes in average temperatures, rainfall and climate extremes with an important impact on soil erosion (floods, drought, etc.), changes in pests and diseases, changes in the quality of soil nutrients, changes in the growing crop season and changes in sea levels.

Crop yields show a strong correlation with temperature change and with the duration of heat or cold waves and differ based on the stages of plant maturity during extreme weather events (Hoffmann, 2013). Change in precipitation patterns enhance water scarcity and associated drought stress for crops and alter irrigation water supplies. In an indirect way, a change in temperature and moisture levels may also lead to a change in the absorption rate of fertilizers and other minerals which determine yield output. In short, a rise in temperature along with a reduction in rainfall reduces crop productivity if both are beyond the threshold that is suitable for crop production (Tirado and Cotter, 2010). According to Ignaciuk and Mason-D'Croz (2014) at the moment climate change is decreasing the yields of cereal crops such as maize, rice and wheat and also of vegetables and this will decrease seriously by 2050 globally. Climate change’s regional impacts are likely to be substantial and variable with some regions benefiting from an altered climate and other being adversely affected. Generally, food crop production is likely to decline in most developing countries and in critical regions (for example, subtropical and tropical areas), whereas agriculture in developed countries may actually benefit if technology is made available and if appropriate adaptive adjustments are done (Ignaciuk and Mason-D'Croz, 2014).

Crop productivity is projected to increase slightly in the mid-to-high latitudes for a local mean temperature increase of up to 1-3°C depending on the crop and then decrease in some regions. At the lower latitudes, especially seasonally dry and tropical regions, crop productivity is projected to decrease for even small local temperature increases (1-2°C), which will increase risk of hunger (Yohannes, 2016). Agriculture is central to the survival of millions of people in many countries in sub-Saharan Africa (SSA). It is the number one provider of employment and livelihoods in developing countries (IPCC, 2007b). Climate change’s impact on agriculture has significant consequences on livelihoods, food production and the overall economies of countries, particularly those with agriculture-based economies in the developing world because agriculture contributes 29 percent of developing countries’ GDP and 65 percent to developing countries’ populations (Padgham, 2009). Lobell et al.’s (2008) study in 12 food-insecure regions of the world reported that climate change could significantly impact agricultural production and food security up to 2030 particularly in sub-Saharan Africa and South Asia due to both changes in mean temperature and rainfall as well as increased variability associated with both. According to Guiteras (2009), climate change is likely to impose significant costs on the Indian economy by affecting crop yields. Liangzhi et al., (2005) investigated the impact of weather on Chinese wheat yields using time series data and showed that an increase in temperature reduced wheat yields.

Based on data from African countries Exenberger and Pondorfer (2011) show that climate change influenced agricultural production in sub-Saharan Africa in an unfavorable way. They further state that the impact of temperature and rainfall are crucial to the point of life-threatening crop failure. Studying the impacts of climate change on Ethiopian agriculture, Evangelista and Burnett, (2013) report that; the country is among those which are at the most risk of climate change impacts on agricultural productivity and food security. Gebreegziabher et al., (2011) maintain that its low adaptive capacity, geographical location and topography make Ethiopia highly vulnerable to the adverse impacts of climate change. In addition, dependency on climate sensitive sectors for livelihood worsens Ethiopia's vulnerability to the impacts of climate change (UNDP, 2001). The country's climate is characterized by a history of extremes such as droughts and floods, increasing trends in temperature and decreasing trends in rainfall with increasing variabilities (Demeke et al., 2011). Over the last decades, the temperature in Ethiopia increased at about 0.2°C per decade while average minimum and maximum temperature has been increasing by about 0.25^{o}C and 0.1^{o}C every decade respectively. Moreover, according to Belliethathan et al., (2009) the mean temperature in Ethiopia is predicted to increase by 0.9 to 1.1^{o}C by 2030, by 1.7 to 2.1^{o}C by 2050 and by 2.7 to 3.4^{o}C by 2080. On the other hand, precipitation remained fairly stable over the last 50 years when averaged over the country with declining trends. However, the spatial and temporal variability of precipitation is high (IPCC, 2007c). MacDonald and Simon (2011) also report that farmers living in Ethiopia's semi-arid and arid lowlands that have less diversified assets and are heavily reliant on rain-fed agriculture are, along with their livestock, particularly vulnerable to climate change. Bezabih et al., (2014a, 2014b) also point out that climate variability and change in Ethiopia has significant impact on different crop yields. Bayrau et al., (2015) show that changes in climate will have an overall significant impact in reducing the productivity of selected crops in Ethiopia.

1.2.2 Farm Performance: Concepts and Measurements

Productivity and efficiency are the most commonly used performance concepts in the field of production. These are seemingly similar and interchangeably used terms but they are two different concepts. In the field of economics, technical efficiency is measured by comparing the observed output against feasible output in the frontier whereas productivity is defined in terms of the rate of output produced per unit of input utilized in the production process (Färe and Grosskopf, 2003). Constructing the feasible ideal output with which the actual output is compared is based on the concept of production function from which the idea of the frontier production function is derived. Efficiency is a relative measurement as it can only be measured with respect to some point of reference; the point of reference is either an ideal level of performance or best practice frontier (Coelli et al., 2005).

1.2.2.1 Productivity: Concepts and Measurements

Productivity is generally understood as the ratio of output to input. In the case of a single input x and a single good output y, the level of productivity is simply the ratio of these two variables. The main difficulty in measuring productivity concerns the aggregation of multiple inputs and multiple outputs to input and output indices. Agriculture is a prime example of a sector where joint production of multiple outputs using multiple resources is common. The agricultural production process can be modeled as the transformation of multiple inputs denoted by vector $\mathbf{x}$ (for example, land, capital, labor, feed and fertilizers) to multiple outputs denoted by vector $\mathbf{y}$ (for example, crops, milk, meat, eggs and vegetables). The input vector $\mathbf{x}$ may contain both economic inputs such as labor and capital and environmental or natural resources such as weather and climate or agro-ecological resources. Further, trying to compare multiple partial productivity indicators can confuse the overall picture and even lead to a misleading assessment of the overall productivity performance.

Agricultural productivity measures are categorized into partial or total measures. Total productivity measures such as total factor productivity (TFP) refer to productivity measures involving all factors of production (Coelli et al., 2005). This type of measurement requires a more systematic aggregation of inputs and outputs to an input index and an output index (respectively) in one way or another. Total productivity measures require having certain productivity indices or aggregately measured quantities. The productivity index theory provides several quantity index formulae which can be used for aggregation. These include the classic Laspeyres, Paasche and Fisher ideal indices; the Törnkvist index; and the Malmquist index and its variants (for example, Malmquist-Bjurek and Malmquist-Luenberger productivity indices). The classic Laspeyres, Paasche and Fisher ideal indices apply the observed prices of inputs and outputs as index weights. The Laspeyres index uses the prices of the base period as index weights whereas the Paasche index uses the prices of the target period. The Fisher ideal index is the geometric mean of the two. The Fisher (1922) ideal index is known to satisfy a number of axiomatic tests (see, for example, Diewert and Nakamura, 2003). The widely used Törnkvist index is a weighted geometric mean where the weights are defined as cost shares for inputs and revenue shares for outputs. The Malmquist index and its variants (for example, Malmquist-Bjurek and Malmquist-Luenberger productivity indices) resolve the aggregation problem by using marginal rates of substitution or transformation, also referred to as shadow prices. In competitive markets, rational profit maximizing firms use inputs such that the marginal rates of substitution are equal to the relative prices of inputs in the market. Hence, the shadow prices are equal to market prices. Therefore, in a competitive market environment, the Malmquist index can be shown to be equivalent to the Fisher and the Törnkvist indices under certain conditions (see, for example, Färe and Grosskopf, 1992). Even though the conditions for the exact equivalence are rather restrictive, the conventional Fisher and Törnkvist indices can provide reasonable approximations of the Malmquist index for firms that operate in a competitive market environment. These methods are non-parametric. Alternatively, TFP can be estimated parametrically based on an estimation of production and cost functions and decomposed into technical changes and economies of scale components (Heshmati, 2003).

For example, in agriculture total factor productivity is a method of calculating agricultural productivity by comparing an index of agricultural inputs to an index of outputs. It is defined as the ratio of the value of output to the value of all inputs used (Nyoro and Jayne, 1999). TFP trends over time are often used to assess net gains from technological changes. Although TFP measures are the most appropriate measures of productivity, they are used less often especially in Africa because TFP measures are difficult to construct in the absence of data on prices and costs of key inputs.

On the other hand, measures of productivity such as labor productivity in a factory; fuel productivity in power stations and land productivity (yield) in farming are often called partial measures of productivity or single or partial factor productivity (PFP) measures. PFP measures hence refer to the amount of output per unit of a particular input such as yield (output per unit of land or output per animal) and labor productivity (output per economically active person or output per agricultural person-hour). Output and yield growth rates remain the most commonly used indicators of productivity growth in agriculture in developing countries (Chilonda et al., 2007). The main weakness of PFP indices is that they do not account for all the inputs used in production or marketing systems. They can provide a misleading indication of overall productivity (performance) when considered in isolation. Based on the type of data that they need and the assumptions that they require different techniques can be applied for productivity analyses.

I focus on the selected PFP measure of land productivity. Land productivity is measured as the ratio of total output harvested per area or value added per unit of agricultural land. I present an analysis of the status and trends of productivity of some of the key food staples in Ethiopia. There are relatively few studies that have analyzed the determinants of agricultural productivity gain in general (Block, 1995). Some studies on productivity mainly focus on understanding whether productivity changes are due to technological changes or due to efficiency gains. The findings have been somewhat mixed; some studies have found that the productivity gains were due to efficiency gains while others found technology progress to be the main driver of productivity gains (Alene, 2000).

1.2.2.2 Efficiency: Measures and Recent Developments

Measuring and explaining technical efficiency is an important topic of research in the field of applied economics. Since the pioneering work of Farrell (1957) various studies have been conducted in efficiency literature to examine efficiency in crop farming in different countries using different methodologies. Most studies are based on Farrell-type measures of efficiency. However, over the years various other methods of estimating production frontiers have also been developed to come up with reliable efficiency measures. These frontier methods vary from econometric (stochastic frontier analysis—SFA) to non-econometric (data envelopment analysis—DEA) methods. The stochastic production frontier (SPF) model which was introduced by Aigner et al., (1977) accommodates different circumstances (Battese and Coelli, 1992, 1995; Jondrow et al., 1982; Kumbhakar, 1991; Pitt and Lee, 1981; Schmidt and Sickles, 1984). SFA has been extensively used for estimating technical efficiencies. In particular, the SPF model is a better fit for an analysis of agricultural efficiencies because of the higher noise as a result of the stochastic nature of the production process and yield variability usually experienced in agricultural data.

However, the efficiency results of such models are sensitive to the way in which they are modeled and interpreted and to the assumptions underlying the models mainly when panel data is used (Kumbhakar et al., 2014, 2015).The main reason for the different assumptions is that when panel data is available, the productive efficiency of a farm is composed of persistent and transient components of efficiency that cannot be captured distinctively by the earlier SPF models. In addition, these models do not treat explicitly unobservable individual/farm effects in inefficiencies thus generating a mis-specification bias. Further, the effects of these factors may be captured by the term 'inefficiency' thereby producing biased efficiency results. Nevertheless, when panel data started being available, panel data models were developed (Colombi et al., 2014; Filippini and Greene, 2016; Heshmati et al., 2017; Kumbhakar et al., 2014; Tsionas and Kumbhakar, 2014) which allow separating the two components of inefficiency along with disentangled heterogeneity effects.

Estimates of persistent inefficiency provide useful information about the farms in the sector because high values of persistent inefficiency are indicators of non-competitive market conditions. This part of productive inefficiency may be due to the presence of structural problems in the organization of the production process of a farm or the presence of systematic shortfalls in managerial capabilities, regulations, inefficient infrastructure or lasting habits of the management to waste inputs. The transient part of inefficiency on the other hand may stem from temporal behavioral aspects of the management or, for example, from a non-optimal use of some inputs or due to the presence of non-systematic management problems that can be solved in the short term without a major policy change. Such a distinction and measurement of the two components of productive efficiency is interesting because it allows the farms to use their resource/cost saving potential in the short as well as the long-run.

A Partial Review of the Panel Data Stochastic Frontier Models

The stochastic frontier (SF) model originally proposed by Aigner et al., (1977) has been used for measuring and comparing the performance of individual production units within a geographic location, an industry or an agricultural sector since its inception. Extensive research in this field has resulted in the rapid development of econometric techniques concerning specifications, estimations and testing issues of the model. These techniques have been rapidly developed and implemented in a large number of areas using mostly cross-sectional and panel data to estimate firm/farm or individual productive efficiencies. The use of panel data models in estimating producers' efficiency led to avoiding some of the problems related to distributional assumptions encountered in the cross-sectional approach.

Panels also give a large number of data points and have the advantage of separating individual and time-specific effects from the combined effect (Heshmati et al., 1995). Another advantage of panel data is that if inefficiency is time-invariant one can estimate inefficiency consistently without distributional assumptions (Schmidt and Sickles, 1984). As discussed by Hsiao (2004), there are many benefits in using panel data, the principal ones being control of individual heterogeneity, having a greater variability, less collinearity between variables, more degrees of freedom and more efficiency. Such models are more capable of identifying and measuring effects that are not detected in cross-section or time series data.

Panel data SF models introduced in the early 1980s assumed technical inefficiency to be individual-specific and time-invariant. That is, inefficiency levels may be different for different producers but they do not change over time, meaning that an inefficient producer never learns to improve over time. This might be the case in some situations where, for example, the soil quality is low and farms lack water sources for irrigation, or inefficiency is associated with managerial abilities and there is no change in management and production technologies for any of the firms during the period of the study (Kumbhakar et al., 2014, 2015).This seems unrealistic, particularly when production or market competition is taken into account. Another drawback of this approach is that firm heterogeneity cannot be distinguished from inefficiency as all time-invariant heterogeneity is confounded by inefficiency. This raises some related questions that need to be considered: whether inefficiency has been persistent over time or whether it is in time-varying units. Another key question that needs to be considered with regard to time-invariant individual effects is whether an individual effect represents (persistent) inefficiency, or whether the effect is independent of inefficiency and captures (persistent) unobserved heterogeneity. The question here is: should one view the time-invariant effects as persistent inefficiencies or as firm-heterogeneity that capture the effects of (unobserved) time-invariant covariates and as such are unrelated to inefficiency?

Related to these key questions, several panel data SF models were developed to include both time-invariant effects and time-varying inefficiencies as discussed in Kumbhakar et al., (2015) and Colombi et al. (2014).Some of these models estimate the persistent part of productive efficiency while others estimate its transient component. The earlier panel data SF models either assumed time-invariant effects as persistent inefficiencies (as in Pitt and Lee, 1981 and Kumbhakar, 1991) or time-varying inefficiencies (for example, Battese and Coelli, 1992; and Lee and Schmidt, 1993) without taking into account the firm effect. The later models either confound the firm effect with persistence inefficiency (Kumbhakar and Heshmati, 1995), or the firm effect is separated from time-varying inefficiency without taking into account the possibility of persistent inefficiency (for example, Greene, 2005a). However, some recently developed panel data SF models provide information on whether a firm is characterized by the presence of both types of productive inefficiencies. Some models also fall between these extreme (Kumbhakar et al., 2014). The models proposed by Kumbhakar (1991) and Kumbhakar and Heshmati (1995), are in between. These models treat firm effects as persistent inefficiency and include another component to capture time-varying technical inefficiency.

Although several panel data SF models discussed earlier can separate firm heterogeneity from transient inefficiency (which is either modeled as the product of a time-invariant random variable and a deterministic function of covariates or distributed i.i.d. across farms and overtime), none/few of these models consider persistent technical inefficiency. Identifying the magnitude of persistent inefficiency is important especially in short panels because it reflects the effects of inputs like management as well as other unobserved inputs which vary across firms but not over time. Thus, unless there is a change in something that affects management practices at the level of a firm (such as changes in ownership or new government regulations); it is unlikely that persistent inefficiency will change. Alternatively, transient inefficiency can change over time without operational changes in a farm. Thus, having information and estimating the persistence and transient components of inefficiency and their separation from unobserved heterogeneity effects is important. Each component provides different information with different policy implications for promoting efficiency in the production of scarce resources.

In an efficiency analysis the technical efficiency scores obtained from efficiency estimating models alone have little use for policy implications and management purposes if the empirical studies do not investigate the sources of the inefficiency. Proponents of determinants of technical efficiency offer insights into key variables for policymaking for optimal resource utilization and this in turn has implications for productivity and improving livelihoods. Given that in reality farm efficiencies (both persistent and transient) systematically differ across farms and over time, this requires a model that can produce not only the magnitude of these inefficiencies but can also explain their systematic differences in terms of some covariates (Lai and Kumbhakar, 2016). Moreover, if inefficiency components are purely random, farmers do not know how to improve their efficiency irrespective of whether the public provides incentives or not. Further, if the persistent inefficiency component of a farm is high, the farm is likely to stay inefficient unless there is a major restructuring (change in management, for example). Perhaps, if inefficiencies are explained by some covariates, then the farmers can possibly change their inefficiency levels by changing those covariates which are specific to their inefficiency components.

A Short Review of Inefficiency Effects Models

Most of the inefficiency effects models in existing literature are subject to controversies. In this regard, despite the fact that the approaches vary to some extent with the methodology employed, the most commonly followed procedure is what is usually referred to as the one-stage or the two-stage approaches. Some authors like Parikh and Shah (1994) estimated SPFs to predict firm/farm level (in) efficiency indices and then regressed these predicted efficiencies on firm/farm specific variables to explain variations in inefficiencies between firms in an industry. To overcome inconsistencies in the assumptions regarding the independence of inefficiency effects in this two-stage estimation procedure, Kumbhakar et al., (1991), Reifschneider and Stevenson (1991) and Huang and Liu (1994) proposed a single-stage SF in which the inefficiency effects are expressed as an explicit function of the vector of firm/farm specific variables and a random error. They suggested a specific model (under SPF models) that allows the estimation of inefficiency scores and simultaneously explains inefficiency effects. Battese and Coelli (1995) generalized Huang and Liu's (1994) model to allow for panel data thus extending the earlier approaches and suggest that technical inefficiency effects could be replaced by a function of explanatory variables that are supposed to explain inefficiency, directly incorporated into the MLE under the one-stage approach SFA models. This model allows the technical inefficiency parameter, and hence technical efficiency, to vary across time in a potentially different, but predictable, manner across firms/farms.

However, as underlined by Reinhard et al., (2002), a two-stage procedure can be used consistently so long as the efficiency scores are calculated from a particular kind of fractional or proportional data generating process (DGP) from the first-stage parameter estimates, instead of being estimated econometrically at the first stage. Further, Hoff (2007) and Banker and Natarajan (2008) note that the choice of the second-stage regression techniques is a researcher's decision to use the desired regression techniques, particularly when the efficiency scores are not generated by a censoring process but are fractional data. For instance, following the fractional or proportional data generating process (DGP) procedure Reinhard et al., (2002) and Madau (2011) used a MLE technique to estimate inefficiency effects parameters in the second-stage regression. Similarly, MacDonald (2008) estimated robust standard errors OLS parameters in his second-stage regression and argued that the Tobit estimation was inappropriate when efficiency scores were not generated by a censoring DGP.

1.3 Findings from Empirical Literature

1.3.1 Empirical Evidence on Impact of Climate/Weather Variations on Crop Productivity

Studies on the impact of climate change on agricultural crop productivity have increased over time with a more recent focus on developing countries in general, and a specific focus on Africa. Most of the studies assess the extent to which adaptation options can lessen the expected impact of climate change. **Yohannes** (2016) reviewed various articles and documents on the relationship between climate change and agriculture. The two-way relationship between the two is of great significance to developing countries due to their large dependence on agricultural practices for livelihoods and their lack of infrastructure for adaptation when compared to developed countries. Agricultural activities are affected by climate change due to their direct dependence on climatic factors. Based on this review, Yohannes (2016) concluded that climate change had a significant negative role particularly for developing countries' farmers.

Ayinde et al., (2010) analyzed climate change and agricultural production in Nigeria using time series data. They used descriptive statistics and a Granger causality test analysis as analytical tools and reported that temperature remained relatively constant and did not affect agricultural output. However, they reported that the Granger causality approach revealed that changes in rainfall positively affected agricultural production in Nigeria.

Lee et al., (2012) analyzed the impact of climate change on agricultural production in 13 Asian countries from 1998 to 2007. Their study used the agricultural production model and estimated a country-level fixed-effects panel model for agricultural production using seasonal climate variables and other input variables. Their results show that higher temperatures and more precipitation in summer increased agricultural production while higher fall temperatures were harmful for crop productivity in South and Southeast Asia. On the other hand, they reported that overall increase in annual temperature decreased agricultural production in Asian countries. The study concluded that adapting to climate change for example by developing new varieties that are more tolerant to higher temperatures was necessary and that increasing investments in agricultural productivity and developing proper adaptation programs or policies were important.

A number of empirical works in the Ethiopian context (Bezabih et al., (2014a, 2014b); Demeke et al., 2011; Deressa and Hassan, 2007; Gebreegziabher et al., 2013; Paul et al., 2013) investigate the impact of climate/weather variations on Ethiopian agriculture at different levels using different research methodologies. Deressa and Hassan (2007) analyzed the economic impact of climate change on crop production by using the Ricardian method. They used country-level survey data and regressed the net crop revenue on climate (rainfall and temperature), household and soil variables. They analyzed the seasonal marginal impact of climate variables temperature and precipitation on the crop net revenue. Their analysis indicates that a marginal increase in temperature during summer and winter had a negative significant effect on net crop revenue per hectare and a marginal increase in precipitation during spring had a positive significant effect on net crop revenue per hectare.

Gebreegziabher et al., (2013) investigated crop-livestock inter-linkages and climate change implications for Ethiopia's agriculture in a broader sense using the Ricardian approach in the Nile Basin during the 2004-05 production years. They analyzed the impact of climate change and weather variations on agriculture, crops and livestock, both separately and taken together. Their findings suggest that a warmer temperature was beneficial for livestock agriculture, while it was harmful for the Ethiopian economy from the crop agriculture point of view. Moreover, they concluded that an increasing/decreasing rainfall associated with climate change was damaging for both the agricultural activities. Bezabih et al., (2014a, 2014b) assessed the impact of weather and climate change measures on households' agricultural productivity measured in terms of crop revenue in the Amhara region of Ethiopia. They used four waves of survey data combined with interpolated daily temperature and monthly rainfall data from the meteorological stations. Their findings show that temperature effects were distinctly non-linear but only when the weather measures were combined with the extreme ends of the distribution of climate measures. In addition, they reported that rainfall generally had a less important role to play than temperature which is contrary to expectations for rain-fed agriculture. According to others like Paul et al.,

(2013) Ethiopia is one of the most at risk countries from climate change impacts on agricultural productivity and food security while Gebreegziabher et al., (2011) report that its low adaptive capacity, geographical location and topography make the country highly vulnerable to the adverse impacts of climate change. In addition, Demeke et al., (2011) show the dependency of most of the population on climate sensitive sectors for livelihood which worsens Ethiopia's vulnerability to the impact of climate change.

1.3.2 Empirical Evidence on Crop Farming Technical Efficiency and its Determents

Studies on efficiency in agriculture have increased over recent decades with a more recent focus on developing countries in general, and a specific focus on agriculture in SSA (Addai and Owusu, 2014; Bamlaku et al., 2009; Fantu et al., 2011; Vedenov et al., 2007). Most of these studies report low to moderate technical efficiencies; thus confirming the evidence that most countries in the developing world in general and in SSA in particular still experience relatively low levels of production efficiency in agriculture.

Vedenov et al., (2007) estimated a translog production function and technical efficiency measures for corn, coffee and other crop farms in Veracruz and Mexico. Their results for technical efficiency from 1997 to 2002 ranged from 0.88 to 0.89. Addai and Owusu (2014) analyzed the sources of technical efficiency of maize farmers across AEZs in Ghana using a stochastic production frontier panel data model. They reported that extension, mono-cropping, land ownership and access to credit positively influenced technical efficiency in production. High input prices, inadequate capital and irregularity in rainfall were the most pressing problems facing maize producers in the forest, transitional and savannah zones respectively.

Although there is a dearth of empirical works on persistent and transient farming technical efficiency and no connection of technical efficiency to weather and/or agro-ecological factors in the Ethiopian context several empirical works have been done to investigate the level of technical efficiency in crop farming at different levels of aggregation using different methodologies. Medhin and Köhlin (2008) employed the stochastic meta-frontier approach to investigate the role of soil conservation in small-scale highland agriculture for four groups of plots. They constructed plot-level stochastic frontiers and estimated meta-frontier technology-gap ratios for three soil conservation technology groups and a group of plots without soil conservation. They reject the stochastic frontier in favor of the stochastic meta-frontier implying that there were significant technological differences among farmers in these groups. They also conclude that farmers found soil and water conservation technology to be more efficient. Abate et al., (2006) tested the effect of farm size on the technical efficiency of teff production using the stochastic frontier production function approach. Their results show that large farms were technically more efficient than small farms. The mean technical efficiency was 0.74 for large farms and 0.68 for small farms. This means that the average level of efficiency of large and small farms was below the frontier by 26 and 32 per cent respectively.

Gebreegziabher et al., (2005) studied the production system of peasant farmers in two districts in Tigray region, northern Ethiopia using the stochastic frontier production function and simultaneously determined farmer-specific technical efficiencies and the determinants of inefficiencies. They found that productivity differences among farmers were relatively small. Their study also shows that land size and oxen ownership were significant contributors to productivity increments, whereas engagement in off-farm activities decreased inefficiency levels significantly.

Bamlaku et al., (2009) investigated efficiency variations and factors causing inefficiency across AEZs in Ethiopia using a stochastic frontier analysis. They show that seasonal climate conditions and agro-ecological settings had a significant impact on technical efficiency. Their study also concluded that education, proximity to markets and access to credit contributed to a significant reduction in farm inefficiencies. Employing a panel data analysis using a stochastic frontier model, Nisrane et al., (2011) analyzed sources of inefficiency and growth in agricultural output in subsistence agriculture. Their results indicate that most of the increase in agricultural output was because of traditional inputs such as size and quality of cultivated land, labor, number of oxen and hoes and was heavily influenced by the amount of precipitation received. They also report that each agro-ecological zone included in the study gained from Hicks-neutral technological improvements during the period and that on average, farming inefficiency consistently declined in the study period. Gebreegziabher et al, (2008) applied the stochastic production frontier method using a single-step efficiency estimation approach to analyze the performance of irrigated and rain-fed smallholder agriculture. They found that farmers were more inefficient on irrigated plots than on rain-fed plots.

Despite a large number of existing productivity and technical efficiency studies, it is still an important area of concern because measuring technical efficiency has relevance for policy interventions. Ethiopia has meager modern resources and less opportunity for adopting better modern technologies. The economy largely depends on rain-fed and very traditional agricultural practices. Therefore, crop productivity and efficiency studies are vital as policy interventions may need to have prior information which will help policymakers decide whether to continue with existing technologies by improving the efficiency of less efficient farmers or introducing new technologies. This research will contribute to this area as it provides up to date information on climate/weather, agro-ecological variations and methodological extensions of the studies quoted earlier.

1.4 The Current Study

1.4.1 Statement of the Problem

Despite recent years of improved growth performance, Ethiopia remains one of the least developed countries in terms of standard development measures including poverty levels (MoFED, 2013; UNDP, 2014). Poverty still remains relatively high in the country due to both rapid population growth and a low starting base. Ethiopia’s agriculture continues to be dominated by the country's numerous small farms that cultivate mainly cereals for both own consumption and sales; smallholders account for 96 percent of the total area cultivated (CSA, 2015). The five major cereals (teff, wheat, maize, sorghum and barley) occupy almost three-quarters of the total area cultivated and accounted for almost 70 percent of total value added in recent years (Ayalew et al., 2014). Climate change and its impact on agricultural productivity and on the other sectors of the economy are multidimensional and complex. In Ethiopia, agriculture crop production is a major source of incomes and livelihoods. Moreover, Ethiopia's crop agriculture is multifarious involving substantial variations in the crops grown across the country's different regions and agro-ecologies.

Major cereals (such as teff, maize, sorghum, barley, wheat and millet) are the core of the country's crop agriculture and are a significant contributor to the country's economy and food security accounting for about 83 per cent of total area cultivated, 89percent of the grain crops produced in the Meher cropping season in 2014-15 and 64 percent of the calories consumed (CSA, 2015). This implies that growth in agricultural productivity directly affects the welfare of a bulk of the rural and urban poor. There has been substantial growth in cereals in terms of the area cultivated, yields and production since the country's GTP I, but the yields are still low by international standards and overall production is highly susceptible to weather shocks. Thus, increasing production levels and reducing variability are essential aspects of improving food security in Ethiopia to help ensure adequate food availability and for increasing household incomes. Ethiopia's crop agriculture in general, and the cereals sub-sector in particular, face serious challenges, even though much of the increase in production in the last few years was due to an increase in the area cultivated. Soil degradation because of erosion in addition to uncertain rainfall distribution and very low levels of irrigation make crop cultivation risky and threaten crop yields.

Ethiopia as an agrarian economy is largely dependent on its agricultural sector to meet its domestic food demand. However, this sector is characterized by poor productivity which makes the country food insufficient. Further, it is widely known that on the national scale, climate variability and its associated effects have been major causes of food shortages and famines in the country. Thus, any variability with regard to climate conditions like rainfall, temperature and soil fertility will predominantly affect the sector's productivity and largely contribute to food shortages and crises (Gebreegziabher et al., 2011). Moreover, as pointed out in the GTP I document (MoFED, 2010) the sector, among others, is facing increasing challenges of climate change, high population pressure and severe environmental degradation. The sector is characterized by inefficiencies and low productivity in which cereals have shown a steady low growth rate in the last two decades (Demeke et al., 2011). Being an agriculturally dependent country with limited capacity for developing and adopting new technologies, increasing production and enhancing farming efficiencies with existing technologies is not a matter of choice but is instead a must for Ethiopia.

In its GTP II document the Ethiopian government underlines that the performance of major crops had been a major contributor to overall growth in agriculture and allied activities (MoFED, 2010; NPC, 2016). GTP II's major agriculture and rural transformation targets are increasing crop production and productivity, promoting natural resource conservation and usage and ensuring food security. By solving the problems of input supply and technology adoption, the plan intends to boost agricultural production by focusing on smallholders and allowing the sector to play a role in stabilizing the economy and supporting the transition to agro-based light manufacturing and agro-allied industrial growth in general (NPC, 2016). GTP II also explains that the factors of production were not efficiently used in the production process and technical efficiency and technological progress of the sector was at a low level. The plan notes that the anticipated productivity and efficiency enhancement in the agricultural crop sector is only possible through enhancing efficient utilization of resources; proper management and dissemination of available technologies; implementing or scaling up best practices of smallholder farmers; and tackling the challenges which have constrained the achievement of farmers' efficiency potential (NPC, 2016).

In this regard after Schultz's (1964) poor-but-efficient hypothesis was proved invalid; most studies on economic growth in developing countries have focused on improving resource use efficiency as an alternative and less costly means of increasing productivity and production efficiency. Further, empirical studies have also shown the existence of widespread inefficiencies among smallholder farmers and recommended ways in which the producers can reallocate their resources for redressing their technical inefficiency levels. Recent research output in the area reveals that low level of productivity and inefficiency in production can arise because of different reasons - time-invariant production heterogeneities (such as land quality) and the effect of varying climatic/weather factors which cannot be removed by institutions/farms themselves. Only a few studies have controlled for these time-invariant effects which potentially affect production primarily due to data limitations.

Recent efficiency studies have also questioned the accuracy of the results of the classic models due to the sensitivity of efficiency results and the way they are modeled and interpreted mainly when panel data is used (Kumbhakar et al., 2014). When panel data is available, productive efficiency can be seen as composed of persistent and transient components which are not captured distinctively by the earlier models. Thus, long term factors exist which cannot be changed by farmers and should not be ruled out from the efficiency term. Hence, recent efficiency studies recommend advanced efficiency modeling that allows distinguishing between long-term fixed factors (heterogeneity) and equally long-term, but alterable persistent inefficiencies, while accounting for the other components of inefficiency. While the distinction between two long-term factors allows more accurate estimation, the additional separation of the two inefficiency components also permits a more elaborate evaluation of policy implications because both components convey different types of information. It is therefore essential to distinguish between influence able short and long-term efficiencies when deducing appropriate policy recommendations for the sector while controlling for exogenous factors. However, technical efficiency scores obtained from efficiency estimating models in efficiency analyses alone have little use for policy implications and management purposes if the empirical studies do not investigate the sources of inefficiency. The proponents of determinants of technical efficiency offer insights into key variables for policymaking for optimal resource utilization which in turn has implications for improving productivity and livelihoods.

Several empirical studies investigate crop productivity and productive efficiency in Ethiopian agriculture and poverty dynamics using different methodologies. A number of studies (for example, Demeke et al., 2011; Deressa and Hassan, 2007; Gebreegziabher et al., 2013 and Paul et al., 2013) investigate the impact of climate/weather variations on Ethiopian agriculture at regional or national levels using different research methodologies. Other studies on Ethiopian agriculture (see, Abate et al., 2006; Gebregziabher et al., 2008 and Vedenov et al., 2007) assess the level of technical efficiency and determinants of crop farming. Numerous studies have also examined the nature and determinants of poverty in Ethiopia a majority of which focus on rural areas **(**Bigsten and Shimeles, 2008; Kedir and McKay, 2005; and Dercon et al., 2005) while a few (Alem et al., 2014 and Tesfaye, 2006) assess urban poverty and others (for example, Ayalew et al., 2014 and Tafesse, 2003) examine the linkages between agricultural productivity and poverty in Ethiopia. However, most of these studies use a static framework and do not assess the extent to which agricultural productivity affects the dynamics of moving in and out of poverty (poor or non-poor; chronic poor or transient poor) to allow comparisons over time. However, despite this large number of climate impact studies on Ethiopian agricultural, there is a dearth of studies linking farm-level cereal productivity to weather factors, and the influence of agro-ecological factors in particular. Moreover, only a few of these studies focus on linking productive efficiency with climate/weather effects or their variations. Most studies pay relatively little attention to assessing the influence of agro-eco-climatic factors and adaptation strategies on farm efficiency in the country.

More importantly, most studies in the efficiency area have ignored farm heterogeneity and have failed to capture its distinctively transient and persistent efficiency components. Thus far only limited attempts have been made to study farming efficiency applying panel data models (for example, Gebreegziabher et al., 2005; Medhin and Köhlin, 2008 and Nisrane et al., 2011) and they use simpler model specification structures of the Battese and Coelli (1992, 1995) type. However, the inherent problem of these models is that farm-specific unobserved heterogeneity is not treated explicitly in farmers' persistent inefficiency in the analyses. This generates a mis-specification bias in the presence of time-invariant unobservable factors (for example, firm-specific innate abilities). The effect of these factors which is unrelated to the production process but which affects output, maybe captured by the inefficiency term thereby producing biased efficiency results. The econometric opportunity to include both arguments (time-invariant heterogeneities and persistent inefficiencies) has emerged just recently. Colombi et al., (2014) established this new specification to separate short and long term perspectives on efficiency changes while controlling for heterogeneity using a 4-error component panel data stochastic frontier (SF) model. While this novel specification has been used in selected areas (see, for example, Filippini et al., 2016 in electricity distribution and Heshmati et al., 2017 for an analysis of international airlines) it was only recently applied to the agricultural sector by Kumbhakar et al., (2012, 2014) using data of grain farmers in Norway and by Rashidghalam et al., (2016) using data for cotton farmers in Iran. Lai and Kumbhakar (2016) extended this model to accommodate factors that can explain both persistent and transient technical inefficiencies. To the best of my knowledge, this has rarely been applied in general and has certainly not been applied to Ethiopian agriculture making this study the first to use the model and extending it to accommodate factors that can explain inefficiency components, including the overall technical inefficiency effects.

A comprehensive analysis of the newly developed efficiency model's specifications including sources of inefficiency differentials is overdue. In addition, the extent and impact of weather variability and the impact due to factors of production including household/farm characteristics on cereal productivity in different AEZs in the country have not been fully understood. Likewise, linkages between agricultural producers, particularly smallholders, and urban consumers is quite important as it can propel economic development and improve food security and nutrition for both rural and urban populations. Therefore, a comprehensive analysis of the productivity and efficiency of farm households and poverty dynamics is overdue.

To address this gap, this thesis analyzes productivity and efficiency of farm households and urban poverty dynamics in Ethiopia at the household level using different panel data modeling techniques; in two broad parts. First, it analyzes poverty using consumption expenditure and poverty dynamics in urban Ethiopia using multiple supplementing and complementing poverty models. Second, it analyzes the productivity and efficiency of smallholder cereal farmers using different specifications and modeling techniques. In particular, the thesis uses a recently proposed panel data stochastic frontier production model in conducting productivity and efficiency analyses to sketch a theoretical model that shows the importance of the distinction between time-invariant farm household heterogeneity, persistent inefficiency and transient inefficiency among cereal farmers in Ethiopia. The research pays particular attention to incorporating farmer-specific characteristics, climate change adaptation strategies and weather and agro-ecological factors in explaining the inefficiency effects.

1.4.2 Objectives of the Dissertation

The general objective of this thesis is to analyze the productivity and efficiency of farms and urban poverty dynamics in Ethiopia at the household level using different panel data modeling techniques.

The specific objectives are to:

i. Investigate determinants of consumption expenditure and poverty dynamics in urban Ethiopia.

ii. Identify the determinants of chronic and transient poverty in urban Ethiopia.
iii. Assess impact of weather variations and influences of agro-ecological differences on cereal productivity.
iv. Estimate persistent, transient and overall technical inefficiencies of cereal the farmers distinguished from heterogeneities using stochastic production frontier model (SFPM).
v. Compare efficiency results with other 3 SFPMs in which one of the specifications is missing.
vi. Assess influences of weather factors on cereal production and productive efficiencies.
vii. Explain persistent, transient and overall technical inefficiencies among smallholder cereal farmers.

1.4.3 Methodological Approaches and Data

Modeling procedures

Various methodological approaches and econometric techniques were employed to fulfill the objectives of the study that suited each specific objective. Based on this the thesis is divided into four inter-related yet independent essays/chapters. The first essay examines determinants of consumption expenditure and poverty dynamics in urban Ethiopia over the period 1994-2009. The other three essays focus on measuring and explaining the efficiency and productivity of cereal producers in rural Ethiopia for the period 1999-2015. The second essay analyzes the effect of weather variations on productivity in particular while the remaining two essays focus on distinguishing farm heterogeneity from persistent and transient efficiency and explaining the variations in farm level efficiencies by socioeconomic, demographic and other forces behind persistent and transient efficiency differentials across cereal producers using stochastic frontier analysis models respectively.

I. Modeling Determinants of Consumption and Poverty Dynamics (Essay I)

The thesis applies the fixed-effects model and quantile regressions (QR)for the poverty analysis to investigate the determinants of consumption expenditure while it uses multinomial logistic regression (MNL) model to identify the determinants of chronic and transient poverty in urban Ethiopia. Methodologically, the study employs real consumption expenditure per capita to measure poverty; it decomposes poverty into categories. Consumption expenditure is prepared according to income due to its closeness to individual needs. For this the research used the Foster-Greer-Thorbecke (FGT) indices to measure the poverty level and both components and Spells approaches to decompose poverty into chronic and transient categories in addition to econometric models.

The essay uses multiple ways of modeling for the econometric analysis and does the analysis in two parts: in the first, it looks at the determinants of per capita consumption expenditure (PCCE) through the robust fixed-effects model (FEM) supplemented by a semi-parametric conditional quantile regression (QR) at different quartiles. FEM is supplemented by the median-based QR as this approach is arguably less sensitive to outliers and provides a more robust estimator in the face of departures from normality in contrast to the mean-based approach. Moreover, QR is robust properties in the presence of heteroscedasticity and it makes no assumption about the distribution of the error in the model (Koenker and Bassett, 1978) and is invariant to monotonic transformations, such as log (.). However, the first type of regression can only identify factors which affect PCCE but they cannot explain why some households are always or sometimes or never poor. Hence, it is important to distinguish chronic poverty from transient poverty in the sense that moving into and out of poverty looks less serious than remaining in poverty. Someone who is poor now, but can reasonably expect to be out of poverty next year is in a better position than someone who is equivalently poor now and who is likely to remain poor in the future.

It is reasonable to view categories of poverty as a nominal variable and use the second type of regression model to investigate the factors affecting either of the poverty categories by taking advantage of a logistic regression. Accordingly, in the second part the essay explores determinants of chronic and transient poverty using a categorical multinomial logistic regression (MNL) model. The two methods/parts are distinct but complementary in an analysis of consumption expenditure, poverty and its dynamics. The first (consumption model) sheds light on the key determinants of consumption expenditure or consumption poverty, while the second (MNL model) provides a picture of poverty categories which helps identify target groups to which the government can direct its poverty alleviation strategies. Together with the MNL model, the three methods allow the identification of the poor and their decomposition into poverty categories and separation from the non-poor segments of the population. Therefore, identifying and estimating the effects of the determinants of household expenditure and poverty categories and their effective use in designing and implementing policies suggest the presence of direct relationships between the three methodologies and their complementarities.

II. Modeling Impact of Weather Variations on Cereal Productivity and Influence of Agro-Ecological Differences in Ethiopian Cereal Production (Essay II)

In Essay II the general conceptual framework of the standard production function (for example, the Cobb-Douglas production function hereafter CDPF) is extended to accommodate for production risks (variations in weather conditions), production environment (operational conditions and practices) and conventional production factors/inputs and farm specific characteristics. The rationale for this is that agricultural crop production requires farmers to produce the maximum output for a given level of possible input use. However, farmers' ability to produce efficiently often depends on production risks (variations in weather conditions), production environment (operational conditions and practices) and farm-specific characteristics (technology selection or managerial practices) that could in turn lead agricultural production and productivity trends to fluctuate over time. Modeling the effect of agricultural inputs on crop production is not as straightforward as the standard production function (for example, CDPF) suggests. The manner in which certain inputs such as damage control inputs, contextual variables (that characterize operational conditions and practices) and production risk factors enter the production function has led people to question the conventional Cobb-Douglas specification. Some studies presume that inputs directly increase potential yields as in CDPF. However, several studies also show that inputs (for example, damage control inputs) do not directly increase potential yield but rather reduce damage to potential yields. Thus, productivity assessment from such differently conditioned production factors/inputs is not as straightforward as that from direct (yield enhancing) inputs.

Lichtenberg and Zilberman (1986) were the first to propose a model to discuss the special nature of damage control inputs as damage-abating inputs (such as pesticides) rather than as crop yield-increasing inputs (like fertilizers), using a built-in damage control function. Subsequently, there has been some debate about the appropriate way to model productivity assessment in agriculture under different operational and risk conditions and practices. Consequently, many studies adapted this study by using a different functional form for the production function and unique estimation procedures noting the importance of factors including weather variables in both the production and damage abatement functions while doing impact and productivity assessments.

Their argument can be used to assess the impact of weather variations, agro-ecological and households' characteristics on crop productivity. For example, a strategy such as increased irrigation or considering weather factors such as changing temperatures or even agro-ecological characteristics like altitude and household characteristics like the age or educational level of the household head cannot enter the production function directly though they have a bearing on the level of production. In the weather/climate change setting this calls for specifying weather factors and agro-ecological factors alongside the usual production function.

This essay hypothesizes that cereal productivity is subject to factors such as direct factors of production, weather factors, farm household demographic and/or socioeconomic characteristics and agro-ecological factors and can be modeled as a composed function of a conventional production function and a function of non-conventional factors of production with a separable structure. Accordingly, the essay uses a combination of a standard production function, production risk and damage control function modeling approach to assess the influence of weather variations and agro-ecological differences on cereal productivity. The essay analyzes unbalanced panel data typically applying a fixed-effects specification that enables keeping the time-variant effects of annual and seasonal weather and at the same time controlling for unobserved time-invariant effects at a farm-household level that potentially lead to an omitted variable bias in cross-sectional Ricardian studies.

III. Modeling Farm Heterogeneity, Persistent and Transient Efficiencies (Essay III)

The third and the fourth essays analyze farmers' efficiency performance using the parametric stochastic frontier analysis (SFA) methodology. In particular, they pay attention to an analysis of farm heterogeneity and persistent and transient productive efficiencies of smallholder cereal farmers. They use a recently developed 4-random error component panel data stochastic frontier model. The model distinguishes between time-invariant farm heterogeneity and persistent and transient inefficiency components.

Since their inception, SPF models have been used for measuring and comparing the performance of individual production units within a geographic location, an industry or farms in the agricultural sector. In particular, the SPF model is a better fit for an analysis of agricultural efficiencies because of the higher noise as a result of the stochastic nature of the production process and because it yields variability usually experienced in agricultural data. While initial studies were limited to cross-sectional data, the use of panel datasets considerably enriched the econometric analysis of SPF models and guaranteed several advantages over cross-section data. Panel data also permits the simultaneous identification of stable long-term (persistent) and varying short-term (transient) technical inefficiency components. Moreover, recent efficiency studies have questioned the accuracy of the results of classic models due to the sensitivity of the efficiency results to the way they are modeled and interpreted and to the assumptions underlying the model mainly when panel data is used (Kumbhakar et al., 2014, 2015).

Recent efficiency studies recommend using advanced efficiency modeling that allows distinguishing between the aforementioned long-term fixed factors (heterogeneity) and equally long-term, but alterable persistent inefficiencies, while accounting for the other inefficiency components. More recently Kumbhakar et al., (2014) and Colombi et al., (2014) presented the first panel data SPF model to include both arguments. They introduced a model that accounts for heterogeneity and persistent inefficiency by splitting the error term into four components -- persistent inefficiency, transient inefficiency, random farm-effects and noise. The econometric opportunity to include both arguments (time-invariant heterogeneities and persistent inefficiency) has emerged just recently. Colombi et al., (2014) and Kumbhakar et al., (2014) established a new specification to separate short and long term perspectives on efficiency changes while controlling for heterogeneity using a 4-error component panel data SF model. While this novel specification has been used in selected areas (see, for example, Filippini et al., 2016 for electricity distribution and Heshmati et al., 2017 for an analysis of international airlines) it has also been applied to the agricultural sector by Kumbhakar et al., (2014) using data of grain farmers in Norway and by Rashidghalam et al., (2016) using data of cotton farmers in Iran. Lai and Kumbhakar (2016) have extended this model to accommodate factors that can explain both persistent and transient technical inefficiencies.

Taking this new econometric modeling opportunity, the third essay estimates cereal farmers' persistent and transient productive efficiencies using different computing model specifications. It uses a 4-random error component panel data stochastic frontier model to distinguish between time-invariant heterogeneity and persistence and transient inefficiencies. It estimates persistent and transient production efficiencies for each farm household and time period controlling for farm heterogeneity. It also compares the results of this model with the other three SPF models in which one of the four components is missing due to their distinct specifications. The models differed in their underlying assumptions of time-variant/invariant efficiencies and their decomposition as well as the separation of technical inefficiencies and farm heterogeneity effects. Accordingly, the essay uses four alternative SPF panel data models. The first model is a basic version of panel data models, the fixed-effects model by Schmidt and Sickles (1984) which assumes inefficiency effects to be time-invariant and individual specific. It thus offers estimates of persistent/long-run inefficiencies. The second model is a true fixed-effects panel data model proposed by Greene (2005a). This separates transient/short-run inefficiencies from persistent individual effects. The third model is a 3-component random error panel data model (Kumbhakar and Heshmati, 1995) that gives estimates of persistent and transient inefficiencies without accounting for farm heterogeneity. The fourth model is a recently developed 4-component error panel data model by Kumbhakar et al., (2014) that provides estimates of persistent and transient inefficiencies separating them from time-invariant farm effects and noise.

IV. Models Explaining Persistent and Transient Technical Inefficiencies (Essay IV)

The fourth essay explains the effects of different determinants on persistent and transient inefficiency and the overall inefficiency effects among smallholder cereal farmers. It extends the 4-component stochastic frontier model to accommodate factors that can explain persistent and transient inefficiency and compute the marginal effects of the determinants on each type of inefficiency component. Such a model not only provides estimates of persistent and transient inefficiency but also generates marginal effects of the determinants of the inefficiencies. The essay uses a mixed efficiency analysis approach in two steps where it first estimates persistent and transient inefficiency scores to explain their differentials. Second, in a two-stage approach it explains the overall inefficiency effects. In line with Lai and Kumbhakar (2016) the essay uses the one-stage SFA approach by extending the 4-error component model to accommodate factors that can explain persistent and transient inefficiency. Using this approach it estimates persistent technical efficiency (PTE) and transient technical efficiency (TTE) scores while simultaneously using the respective inefficiency effects models and computing the marginal effects of the determinants on each type of inefficiency.

Moreover, to examine the effects of omitting weather factors in model specifications, on technical inefficiency estimates and correlates of technical inefficiency effects, the essay estimates the production frontier with and without the weather variable. It uses a two-stage approach to explain the overall technical efficiency (OTE) differentials. Here the OTE scores are estimated as a product of PTE and TTE from the first stage efficiency estimates and these are successively regressed on the covariates at the second-stage using panel data models. It uses

Reinhard et al., (2002) and MacDonald's (2008) recommendations to account for the inconsistencies in the assumption of inefficiency parameter distribution in the second-stage regression. To explain factors that can affect OTE in the second-stage regression it applies regression techniques such as POLS and panel data models with (respectively) fixed and random effects panel regression methods. It also makes a MLE, the two-limit Tobit random-effects regression using censored efficiency values for comparison purposes.

1.4.4 Data and the Study Area

This thesis uses two distinct panel datasets (EUHS and ERHS) both surveyed at the household level in collaboration with national and international institutions; data was collected in different survey waves.

For the poverty analysis it uses five rounds survey data from the Ethiopian Urban Household Survey (EUHS) dataset covering 1994-2009. EUHS is a panel dataset that has several socioeconomic variables on the individual and household levels collected in 1994, 1997, 2000, 2004 and 2009 by the Department of Economics, Addis Ababa University (AAU) in collaboration with the Department of Economics, the University of Gothenburg and the Michigan State University. The data covers seven major cities– capital Addis Ababa, Awassa, Bahir Dar, Dessie, Dire Dawa, Jimma and Mekelle which were believed to represent major socioeconomic characteristics of the urban population in Ethiopia. Before a household was chosen, a numbered list of all urban households was obtained from urban administrative authorities and then households were selected randomly from half of the kebeles in districts. Once the list was constructed, stratified random sampling was used to set sample size for each city and for selecting sample households in each kebeles whereby in each study cities was represented in proportion to its population making a total of 1,500 households assumed to represent the urban population. After the sample size for each city was decided, the due sample size was distributed over all districts in each urban center.

The last round of the survey was conducted from the original sample by forming a sub-sample of the original sample covering four cities: Addis Ababa, Awassa, Dessie and Mekelle following a similar sampling strategy, comprising about half of the original sample. The sub-sample was checked and verified to represent the major urban areas as well as the original sample (Alem and Söderbom, 2012). Hence, for analysis this thesis used five rounds of data from seven cities forming a total of semi balanced 566 panel households consisting of 2,630 observations. The dataset was comprehensive and it addressed household living conditions including income, expenditure, demographics, educational status, occupation, production activities and other variables at the household and individual levels.

Data for farm productivity and efficiency which was used for the analysis (the other three essays of the thesis) was sourced from the four rounds of the Ethiopian Rural Household Survey (ERHS), which is a panel dataset covering eight villages in rural Ethiopia for the period 1999-2015. This dataset (commonly known as ERHS) is a longitudinal dataset collected from randomly selected 18 farmer associations (FAs) at the farm household level in rural Ethiopia. The Department of Economics at Addis Ababa University, Centre for the Study of African Economies, and University of Oxford, UK in collaboration with the International Food Policy Research Institute collected and supervised the data. Data collection started in 1989 in seven study sites in northern Ethiopia with a sample size of 450 households. The 1989 survey was expanded in 1994 by incorporating other sites indifferent regions. From 1994 onwards, data collection was done in a panel framework. The number of study areas was increased to 15 with the resulting sample size totaling 1,477 households. The newly included villages were selected to represent the country's diverse farming systems. Further, three more FAs was included in ERHS rounds 1999, 2004 and 2009 to represent high productivity areas making a total of 18 FAs in rural Ethiopia. Before a household was chosen, a numbered list of all households (sampling frame) was developed with the help of the local FA's authorities. Once the list was constructed, stratified random sampling was used for selecting sample households in each village whereby in each study site the sample size was proportionate to the population resulting in a self-weighing sample (Dercon and Hoddinott, 2004).

The last round was extended from the original sample by forming a sub-sample of the original sample covering eight FAs following a similar strategy. This now comprised of 503 farm households and was conducted by the researcher in 2015 with financial support from the Environment for Development (EfD) initiative at the University of Gothenburg, Sweden. The survey sites included FAs in Amhara and Oromia regional states, regions that represented the largest proportion of predominantly-settled farmers in the country. The eight FAs were selected carefully to represent the major cereal producing areas that may represent different AEZs in the country. These FAs are characterized by a mixed-farming system. The content of the questionnaire was extracted from ERHS and it focused only on those parts which were required for the intended study. The overall dataset was comprehensive and addressed farm-households' demographic and socioeconomic characteristics; production inputs and outputs; and access to institutions. Important secondary data needed for the study like FAs' geographical location, elevation and metrological data on weather variables was obtained from the Ethiopian Meteorology Authority. The metrological dataset includes daily observations of rainfall and maximum and minimum temperature collected in stations close to the study villages in 1994-2015.

Hence, the productivity and efficiency analysis used four (1999, 2004, 2009 and 2015) rounds of data forming 446 semi-balanced panel households consisting of 1,648 observations that were surveyed from eight FAs. The four rounds were selected to allow for even time spacing and covering approximately a similar time frame for data collection. The 1994 survey was excluded as it misses most of the important variables used for the analysis.

1.4.5 Contributions of the Study

This thesis analyzes productivity and efficiency of farm households and urban poverty dynamics in Ethiopia using a household level panel dataset. It consists of four inter-related chapters/essays, the first of which examines urban poverty dynamics over the period 1994-2009. The other three focus on analyzes of productivity and productive efficiency of farm households. The third essay analyses the effects of weather variations and influence of agro-ecological differences on cereal productivity, while the other two focuses measuring and explaining efficiency of cereal farmers; using stochastic frontier analysis methodology over the period 1999-2015. In doing this, the research contributes to the field of applied economic analysis in a number of ways besides providing well documented policy recommendations which are useful not only for academicians but also for policymakers.

The first essay contributes to poverty literature by investigating the welfare/PCCE movement and poverty dynamics of urban households over time using standard poverty measures and poverty decomposition methods for studying transient and chronic poverty status. The study contributes to poverty literature through its analysis of poverty, employing alternative econometrics techniques to corroborate the results by compensating for their limitations and their complementarities. By filling this gap, the study contributes to urban poverty literature in Ethiopia by providing evidence on relevant correlates of both PCCE and poverty from both household head's characteristics and household characteristics.

The thesis contributes to the existing literature on climate change impact, productivity and efficiency analysis in several aspects. The second essay in particular contributes to the impact of climate change on crop productivity. First, while the effects of annual and seasonal weather variations capturing short term patterns are likely to differ from long term patterns of climate change, these possible differentials have not been thoroughly assessed in previous studies on Ethiopia. Secondly, this research makes an important contribution to existing methodologies in its approach by employing a combination of standard production function, production risk and damage control framework approach as its model. It incorporates environmental variables (land quality, weather and agro-ecology) and other exogenous factors over a shorter period of time in productivity analysis/models as opposed to long-term average climate variables normally used in a Ricardian analysis; so it makes an important methodological contribution. It analyzes unbalanced panel data typically applying a fixed-effects model that enables keeping the time-variant effects of annual and seasonal weather and at the same time controlling for unobserved time-invariant effects at a farm-household level that potentially lead to omitted variable bias in cross-sectional Ricardian studies. It uses the AEZ analysis for cereal cropping activities on a farm and is therefore replicable elsewhere in the country, between regions and within AEZs. This essay thus contributes in providing valuable information which is needed for developing agro-ecologically adaptive strategies in response to the impact of climate change on crop production with growth, poverty and food security implications.

The third and fourth essays focus on measuring and explaining the efficiency of cereal producers using stochastic frontier analysis models. The two essays focus on distinguishing farm heterogeneity from persistent and transient efficiency and explaining the variations in efficiency by socioeconomic, demographic and other forces behind persistent and transient efficiency differentials across cereal producers respectively. These two essays raise research questions that are considered for the first time for Ethiopia. In these two essays the thesis addressed for the first time in Ethiopia's crop farming, the following issues in efficiency analysis: controlled for time-invariant (Heterogeneity & inefficiency) effects in efficiency evaluation, decomposed (in) efficiency into (persistent & transient components) distinguished from heterogeneities.

Hence, the third essay contributes to existing literature as it provides one of the first empirical analyses to show the presence of persistent and transient inefficiencies using a novel econometric approach -- a 4-component random-error panel data SF model -- for Ethiopia's smallholder cereal farmers. Second, to the best of the researcher's knowledge this is the first panel data analysis which addresses the problems of individual and farm heterogeneities in measuring production efficiencies in Ethiopia's crop farming that disentangles farm heterogeneity from inefficiency effects. Thus, it provides valuable information on persistence and transient inefficiency and farm heterogeneity effects. Third, it does an analysis based on agro-ecological zones (AEZs) which considers cereal farming at the farm-household level and thus it also considers output. Therefore, it is replicable elsewhere in the country, between regions and within AEZs.

The fourth essay contributes to efficiency literature as it extends a 4-error component FS panel data model to accommodate factors that can explain inefficiency components in Ethiopia's crop farming. It explained persistent, transient & overall (in) efficiencies, for the first time. In addition, this essay includes weather factors in efficiency estimating production/frontier models and also in inefficiency effect explaining models; to examine the weather factors effect on efficiency estimate and their covariates. In particular, the essay estimates the production frontier with and without the weather variables' specifications to examine the effects of omitting weather factors in model specifications, on technical efficiency estimates and correlates of technical inefficiency effects. It also explains technical inefficiency for both specifications (with and without the weather factors) and compares the results using different regression techniques. Hence, it contributes to another modeling approach which includes climate variables thus improving the precision with which one can estimate and explain technical inefficiency. The essay is also unique in the methods that it uses to explain persistent, transient and the overall technical inefficiency. It uses a mixed efficiency analysis approach in two steps. First, it estimates persistent and transient inefficiency scores and simultaneously explains their differentials using the extended 4-component stochastic frontier model. Second, it explains the overall inefficiency effects in a two-stage approach.

Moreover, the study incorporates climate change adaptation strategies, weather and agro-ecological factors to explain inefficiency in addition to the usual farmer-specific characteristics in similar studies in Ethiopia. Thus, it identifies a number of key policy-relevant technology shifters by examining their effects on inefficiency components from which the policy implications are drawn. Overall, this research makes a significant contribution to the limited literature on agro-eco-climatic factors and adaptation strategies on productive efficiency in least developed countries (LDCs) in general and in Ethiopia in particular.

1.5 Summary of the Dissertation

This thesis analyzes production efficiency of farm households and urban poverty in Ethiopia using household level panel datasets. It consists of four inter-related essays, the first of which examines urban poverty dynamics over the period 1994-2009. The other three essays analyze productivity and efficiency of smallholder cereal farmers in rural Ethiopia using survey data with five years intervals for the period 1999-2015.The analyses in these essays are based on a panel sample of smallholder farm-households across eight FAs in rural Ethiopia using four rounds of data from the ERHS dataset. The second essay specifically focuses on analyzing the effects of weather variations while the other two analyze productive efficiency of cereal farmers using the parametric stochastic frontier analysis (SFA) methodology. The efficiency analysis focus on measuring farm heterogeneity distinguished inefficiency estimates decomposed into (persistent and transient inefficiency) components; and explaining the effects of socioeconomic and demographic determinant factors and the forces behind persistent and transient efficiency differentials across cereal producers respectively.

The first essay analyzes determinants of consumption expenditure and poverty dynamics in urban Ethiopia using five rounds of panel data in a time range from 1994 to 2009. It employs consumption expenditure to measure poverty levels. It uses the fixed-effects model and quantile regression to investigate determinants of consumption expenditure at mean and different quartiles and the MNL model to assess determinants of chronic and transient poverty. In addition, it uses the Foster-Greer-Thorbecke indices to measure the intensity of poverty and both the component and Spells approaches to decompose poverty into categories. Consistent with previous findings of poverty studies in sub-Saharan Africa, my findings show that while a large number of households frequently moved in and out of poverty between the panel periods, many did not move far above the poverty line and remained vulnerable to falling back into poverty. Poverty indices show that poverty incidence, depth and severity consistently declined overtime. The Spells approach measurement indicates that more than 8 per cent of the households were trapped in chronic poverty while 56 per cent were affected by transient poverty. The results of the fixed-effects and quantile regressions on firm that gender, age, primary, secondary and tertiary education and employment of the household head, remittances and location of the household were important determinants of household's consumption expenditure. MNL's results show that a female-headed household was significantly positively associated with both chronic and transient poverty. Primary, secondary and tertiary schooling and employment of the household head, remittances and location of residence all significantly reduced chronic and transient poverty. Household size, dependency-ratio and casual-workers aggravated poverty categories. Age showed a positive effect on chronic poverty while it had an opposite effect on transient poverty.

The second essay assesses the influence of weather variations and agro-ecological differences on cereal productivity. It extends the standard production function to accommodate production risks (such as variations in weather conditions), production environment (operational conditions and practices) along with conventional production factors/inputs and farm specific characteristics in its modeling. It analyzes a semi-balanced panel data typically applying a fixed-effects model that enables keeping the time-variant effects of annual and seasonal weather and at the same time controlling for unobserved time-invariant effects. Consistent with previous findings of productivity studies in SSA, which primarily consider conventional agricultural production inputs and climate factors, my results confirm the importance and statistically strong dependence between most of the explanatory variables and cereal production efficiency.

The third essay analyzed farm-heterogeneity, persistent and transient productive efficiencies of the cereal farmers using different computing model specifications. It uses a 4-random error component stochastic frontier model to distinguish between time-invariant farm heterogeneity and persistence and transient inefficiency. It estimates persistent and transient productive inefficiency for each farm household and time period controlling for farm heterogeneity. This model is compared with three other restrictive computing panel data stochastic frontier models in which one of the four components is missing. The models differ in their underlying assumptions of time-variant/invariant efficiencies and their decomposition as well as the separation of technical inefficiencies and farm-heterogeneity effects.

The fourth essay explains persistent and transient and the overall inefficiency effects among smallholder cereal farmers. It extends the 4-component stochastic frontier model to accommodate factors that can explain persistent and transient inefficiency and computes the marginal effects of the determinants on each type of inefficiency component. It uses a mixed efficiency analysis approach in two steps. First, it estimates persistent and transient inefficiency scores and simultaneously explains their differentials using the extended 4-component stochastic frontier model. Second, it explains the overall inefficiency effects in a two-stage approach. Using this approach, it estimates the overall efficiency scores as a product of persistent and transient efficiency scores from the first stage efficiency estimates and regresses them on the covariates at the second-stage using the panel data estimation method. The descriptive results show that cereal production and productivity increased over time in the study area and in each agro-ecological zone while efficiency estimates consistently declined over time. Average annual rainfall distribution trends declined while average annual temperature increased over time in the study period.

Econometrics results of the productivity analysis indicate that agro-chemicals, livestock, number of plots, education and agricultural extension services significantly enhanced cereal productivity while land quality and household-head's age significantly influenced cereal productivity negatively. The regression results show that annual and seasonal weather variations, both in their linear and quadratic terms significantly influenced cereal productivity. Annual rainfall significantly enhanced cereal productivity while precipitation in summer, fall and spring seasons significantly and negatively influenced it. On the other hand, fall and spring temperatures significantly enhanced cereal productivity while annual temperature and the summer season had a significant negative impact. Moreover, the results give evidence of agro-ecological differences. The results confirm that more productive production is likely to be in higher altitudes where rainfall and temperature are favorable for cereal production.

Empirical results from the translog production frontier parameters (MLE) across models indicate that agro-chemicals, livestock, machinery and labor significantly enhanced cereal production. Estimates of production elasticities indicate that each input contributed significantly to enhancing cereal production levels. The results of efficiency estimates across models indicate that the mean and dispersion of efficiencies among farmers differed by the model's specifications and their agro-ecological zones and sub-zones. Thus, the study confirms the importance of evaluating technical efficiency using distinct specifications and demonstrates how efficiency estimations are sensitive to model specifications. This was confirmed by Kendall's rank correlation coefficients as the models generated similar and consistent efficiency estimates. The results also show that cereal farming was technically regressed at an increasing rate and exhibited increasing returns to scale over time. The empirical results show that cereal farming in the study area was characterized by the presence of both transient and persistent productive inefficiencies. Further, the results show that cereal growing farmers experienced much more short-term and transient inefficiency problems as compared to long-term and persistent inefficiency. The overall implications of the results of the efficiency level analyses are that cereal farmers were highly inefficient and there is room for improvement at the present state of technology use.

The results of the inefficiency effects models reveal that most of the farmer specific characteristics, adaptation strategies and agro-ecological and climatic factors had significant effects in determining cereal farming technical (in) efficiencies with different magnitudes. In particular, the empirical results of MLE show that transient efficiency was enhanced by gender, household size and number of plots, while it was significantly negatively influenced by age, secondary schooling and temperature variations. Persistent inefficiency was negatively influenced by altitude and ecological factors. Overall efficiency was significantly enhanced by farm size, gender, household size, remittances, improved adaptation strategies and weather and ecological factors. It was negatively significantly influenced by credit use, age, territory, schooling, off/non-farm activities and extreme weather variations. Further, the study also examined the effects of omitting weather factors in model specifications on estimates of technical inefficiency and correlates of technical inefficiency effects by estimating the production frontier with and without the weather variables. The research shows that the omission of weather factors from specification affects not only reduced the model's precision, but also resulted in biased inefficiency scores and estimates of determinants.

These findings are important and can be used to initiate the government's developmental policy options for poverty reduction, in planning climate change adaptation strategies and in agricultural policies; agricultural policies that are tailored to enhance productive farming efficiency and productivity improvements and while planning weather/climate change adaptation and poverty reduction strategies to support various agro-ecological zones across the country. Having poverty and food security implications, the research therefore recommends public policies that improve the supply of modified agricultural inputs and sustain improved climate change adaptation strategies which are suitably designed to suit the needs of farmers and agro-ecological zones' peculiarities to enhance short-term and long-term productive efficiencies of cereal farming in Ethiopia. Further, policies that incorporate poverty reduction strategies and targeting will be more effective if they take into consideration household head and household characteristics while supporting the poor and tackling poverty incidences. Policies that encourage remittances, a smaller household size and improving access to education and employment activities will exert a positive effect on consumption expenditure and thus help in reducing urban poverty. Household heads' and households' characteristics are important to alleviate either of the poverty categories or in framing poverty reduction strategies.

References

Abate, B., F.V. Machel, and A. Gezahegn (2006). Effect of Farm Size on Technical Efficiency of Teff Production: A case Study of the Moretina Jiru District, Central Ethiopia. *Ethiopian Journal of Development Research*, 27 (1).

Addai, K. and V. Owusu (2014). Technical efficiency of maize farmers across various AEZs of Ghana. *Journal of Agriculture and Environmental Sciences*, 3(1): 149-72.

African Development Bank (AfDB) (2016). *Federal Democratic Republic of Ethiopia: Country Strategy Paper-CSP, 2016-20.*

Aigner, D., C. A. K. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production model. *Journal of Econometrics*, 6(1): 21-37.

Alem, Y. and M. Soderblom (2012). Household level consumption in Urban Ethiopia: The effects of a large food price shock. *World Development*, 40(1): 146-62.

Alem, Y., G. Kohlin, and J. Stage (2014). The Persistence of Subjective Poverty in Urban Ethiopia. *World Development*, 56: 51-61.

Alene, A.D. (2000). Productivity Growth and the Effects of R&D in African Agriculture. *Agricultural Economics*, 41:223-38.

Ayalew Z. A, B. A. Alemu, and M. A. Hanjra (2014). Policies for Agricultural Productivity Growth and Poverty Reduction in Ethiopia. *World Development*, 59: 461–74.

Ayinde, O. E., M. O. Adewumi, and V. Ojehomon (2010). ‘Determinants of Technical Efficiency and Varietal-Gap of Rice Production in Nigeria: A Meta-Frontier Model Approach’, International Association of Agricultural Economists Conference, Beijing, China.

Bamlaku B.A., E.A. Nuppenau, and H. Boland (2009). Technical Efficiency of Farming Systems across Agro Ecological Zones in Ethiopia: An Application of Stochastic Frontier Approach. *Agricultural Journal*, 4(4): 202-7.

Banker, R. D. and R. Natarajan(2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research*, 56: 48-58.

Battese, G.E. and T.J. Coelli (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis*, 3: 153-69.

Battese, G.E. and T.J. Coelli (1995). A Model for Technical Inefficiency in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20: 325-32.

Bayrau, A., B. Assefa, and A. Hagos (2015). *Productivity and welfare impact of climate change in sugarcane and cotton producing regions of Ethiopia. EDRI Research Report 23.* Addis Ababa: Ethiopian Development Research Institute.

Belliethathan, S., Y. Tibebe, and W. Girum (2009). *The Impact of Climate Change on Millennium Development Goals (MDGs) Implementation in Ethiopia*. Poverty Action Network of Civil Society Organizations in Ethiopia: A desk review.

Berhanu, A. and M. Zeller (2011). *Impacts of Rainfall Shock on Smallholders Food Security and Vulnerability in Rural Ethiopia: Learning from Household Panel Data.* Stuttgart, Germany: Department of Agricultural Economics and Social Sciences in the Tropics and Sub tropics (490a), University of Hohenheim.

Beyan, A., H. Jema, and G. Endrias (2013). Analysis of Farm Households' Technical Efficiency in Production of Smallholder Farmers: The Case of Girawa District, Ethiopia. *American-Eurasian Journal of Agricultural and Environmental Science*, 13(12): 1615-21.

Bezabih M., S. Di Falco, and M. Alemu (2014a). On the Impact of Weather Variability and Climate Change on Agriculture: Evidence from Ethiopia. Environment for Development and Resource for the Future. Discussion Paper series, 14-15.

Bezabih, M., S. Di Falco, and M. Alemu (2014b). Is it the climate or the weather? Differential economic impacts of climatic factors in Ethiopia. Centre for Climate Change Economics and Policy. Working Paper No. 165.

Bigsten, A. and A. Shimeles (2008). Poverty transition and persistence in Ethiopia. *World Development*, 36(9): 1559-84.

Block, S.A. (1995). The Recovery of Agricultural Productivity in Sub-Saharan Africa. *Food Policy,* 20(5): 385-405.

Central Statistical Agency (CSA) (2007). *Country Population and Housing Census Report-2007*. Addis Ababa: MoFED.

Central Statistical Agency (CSA) (2014). *Agricultural sample survey (AgSS 2013-2014).*Report on area and production of major crops, private peasant holdings, Meher season, Volume I, Addis Ababa: MoFED.

Chauvin, N. D., F. Mulangu, and G. Porto (2012). *Food production and consumption trends in sub-Saharan Africa: Prospects for the transformation of the agricultural sector. Addis Ababa: UNDP WP 2012–11. UNDP, Regional Bureau for Africa.*

Chilonda, P., C. Machethe, and I. Minde (2007). Poverty, food security and agricultural trends in southern Africa. ICRISAT, IFPRI and IWMI.

Coelli, T. J., Rao, D. P., O'Donnell, C. J., & Battese, G. E. (2005). Introduction to efficiency and productivity analysis. USA: Springer Science Business Media Inc.

Colombi, R., S.C. Kumbhakar, G. Martini, and G. Vittadini (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis,* 42: 123-36.

Demeke, A. B., K. Alwin, and Z. Manfred (2011). Using panel data to estimate the effect of rainfall shocks on smallholders' food security and vulnerability in rural Ethiopia. *Climatic Change*, 108: 185–206.

Dercon, S. and J. Hoddinott (2004). *The Ethiopian Rural Household Surveys: Introduction.* Washington, DC: International Food Policy Research Institute.

Dercon, S., J. Hoddinott, and T. Woldehanna (2005). Shocks and consumption in15 Ethiopian villages: 1999-2004. *Journal of African Economies*, 14(4): 559-85.

Deressa, T. and R.M. Hassan (2007). Economic Impact of Climate Change on Crop Production in Ethiopia: Evidence from Cross-section Measures. *Journal of African Economies*, 18(4): 529–54.

Diewert, W.E. and A.O. Nakamura (2003). Index Number Concepts, Measures and Decompositions of Productivity Growth. *Journal of Productivity Analysis,*19(2–3): 127–59.

Evangelista, P. N. and Y. N. Burnett (2013). How will climate change spatially affect agriculture production in Ethiopia? Case studies of important cereal crops. *Climatic Change*, 119: 855-73.

Exenberger, A and P. Andreas (2011). *Rain, temperature and agricultural production: The impact of climate change in Sub-Sahara Africa, 1961-2009, Working Papers in Economics and Statistics, No. 2011-26.*Austria: University of Innsbruck.

Färe, R. and S. Grosskopf (1992). Malmquist Productivity Indexes and Fisher Ideas Indexes, *Economic Journal*, 102: 158–60.

Färe, R. and S. Grosskopf (2003). Non-parametric Productivity Analysis with Undesirable Outputs: Comment. *American Journal of Agricultural Economics*, 85: 1070–74.

Farrell, M.J. (1957). Measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3): 253–81.

Filippini, M. and W.H. Greene (2016). Persistent and transient productive inefficiency: A maximum simulated likelihood approach. *Journal of Productivity Analysis*, 45(2): 187-96.

Fisher, I. (1922). *The Making of the Index Numbers.* Boston: Houghton Mifflin.

Food and Agriculture Organization (FAO) (2016). *Federal Democratic Republic of Ethiopia: Country Programming Framework-CPF*, 2016-20. Italy: FAO.

Gebreegziabher, Z., A. Mekonnen, R. Deribe, S. Abera, and M. M. Kassahun (2013).Crop-Livestock Inter-linkages and Climate Change Implications for Ethiopia's Agriculture: A Ricardian Approach, EfD Discussion Paper 13-14.

Gebreegziabher, Z., A. Oskam, and T. Woldehanna (2005). Technical Efficiency of Peasant Farmers in Northern Ethiopia: A Stochastic Frontier Approach, in proceedings of the 2nd International Conference on the Ethiopian Economy, Addis Ababa, Ethiopia.

Gebreegziabher, Z., S. Jesper, A. Mekonnen, and A. Alemu (2011). Climate Change and the Ethiopian Economy: A Computable General Equilibrium Analysis. EfD-DP-11-09.

Greene, W. (2005a). Reconsidering heterogeneity in panel data estimators of the stochastic frontier models. *Journal of Econometrics*, 126(2): 269–303.

Guiteras, R. (2009). The Impact of Climate Change on Indian Agriculture, Mimeo. University of Maryland.

Heshmati, A. (2003). Productivity Growth, Efficiency and Outsourcing in Manufacturing and Services. *Journal of Economic Surveys*, 17(1): 79-112.

Heshmati, A. (ed.) (2016). *Poverty and Well-Being in East Africa: A Multi-faceted Economic Approach*. Switzerland: Springer.

Heshmati, A. (ed.) (2017). *Economic Transformation for Poverty Reduction in Africa: A Multidimensional Approach*. London: Routledge.

Heshmati, A., S.C. Kumbhakar, and J. Kim (2017). Persistent and Transient Efficiency of International Airlines. *European Journal of Transport and Infrastructure Research*, forthcoming.

Heshmati, A., S.C. Kumbhakar, and L. Hjalmarsson (1995). Efficiency of Swedish pork industry: A farm level study using rotating panel data 1976-1988. *European Journal of operational Research*, 80: 519-33.

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modeling the DEA scores. *European Journal of Operational Research*, 181: 425-35.

Hoffmann U. (2013). "Agriculture: a key driver and a major victim of global warming", in Hoffmann 2013, Section B. Lead Article: 3-5.

Huang, C.J. and J.T. Liu (1994). Estimation of a non-neutral stochastic frontier production function. *Journal of Productivity Analysis,* 5: 171–80.

IFPRI (International Food Policy Research Institute), (2017). *International Food Policy Research Institute, Washington, DC.*

Ignaciuk, A. and D. Mason-D'Croz (2014). Modeling Adaptation to Climate Change in Agriculture. *OECD Food, Agriculture and Fisheries Papers*, 70: 58.

IPCC (2007b). Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change-Summary for Policymakers.

IPCC (2007c). Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

IPCC (2012). Managing the risks of extreme events and disasters to advance climate change adaptation; a special report of working groups i and ii of the IPCC. Technical report.

IPCC (2014). Climate Change and Water. IPCC Technical Paper VI.

IPCC (Intergovernmental Panel on Climate Change) (2007a). 'Climate Change 2007—thephysical science basis', Contribution of Working Group I to the Fourth Assessment Report of the IPCC. Cambridge, UK.

Jondrow, J., C.A.K. Lovell, I. S. Materov, and P. Schmidt (1982). On the estimation of technical inefficiency in stochastic frontier production model. *Journal of Econometrics*, 19: 233-38.

Kedir, M. and A. McKay (2005). Chronic poverty in urban Ethiopia: Panel data evidence. *International Planning Studies*, 10(1): 49-67.

Koenker, R. and G. Basset(1978). Regression quantiles. *Econometrica*, 46(1): 1-26.

Kumbhakar, S.C. (1991). Estimation of technical inefficiency in panel data models with firm- and time-specific effects. *Economics Letters*, 36: 43-48.

Kumbhakar, S.C. and A. Heshmati (1995). Efficiency measurement in Swedish dairy farms: An application of rotating panel data. *American Journal of Agricultural Economics*, 77: 660–74.

Kumbhakar, S.C., G. Lien, and J.B. Hardaker (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis*, 41(2): 321-37.

Kumbhakar, S.C., H. J. Wang, and A.P. Horncastle (2015). *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*. NY: Cambridge University Press.

Kumbhakar, S.C., S. Ghosh, and J.T. McGuckin (1991). A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business and Economic Statistics*, 9: 279–86.

Lai, H.P. and S.C. Kumbhakar (2016). Panel Data Stochastic Frontier Model with Determinants of Persistent and Transient Inefficiency, Economics seminars papers, New York.

Lee J., D. Nadolnyak, and V. Hartarska (2012). Impact of Climate Change on Agricultural Production in Asian Countries: Evidence from Panel Study, Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Birmingham.

Lee, Y. and P. Schmidt (1993). 'A production frontier model with exible temporal variation in technical inefficiency', in H. Fried and K. Lovell (eds), *The measurement of productive efficiency: techniques and applications*. New York: Oxford University Press.

Liangzhi, Y, M.W. Rosegrant, C. Fang, and S. Wood (2005). Impact of Global Warming on Chinese Wheat Productivity, EPT Discussion Paper 143, IFPRI.

Lichtenberg, E., and D. Zilberman (1986). The Econometrics of Damage Control: Why Specification Matters. *American Journal of Agricultural Economics,* 68: 261–73.

Lobell, D. B., M. B. Burke, C. Tebaldi, M. D. Mastrandrea, W. P. Falcon, *and* R. L. Naylor (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science,* 319*:* 607–10.

Madau, F. A. (2011). Parametric Estimation of Technical and Scale Efficiencies in Italian Citrus Farming. *Agricultural Economics Review*, 12 (1): 91-112.

McDonald, J. (2008). Allowing for different frontier and sub-frontier relationships in second stage DEA efficiency analyses. Flinders Business School, Adelaide.

McDonald, M. and J. Simon (2011). Climate, food security, and growth Ethiopia's complex relationship with livestock, *Policy Brief* 3.

Medhin, H. and G. Köhlin (2008). Soil conservation and small-scale food production in Highland Ethiopia: A stochastic meta-frontier approach. Environment for Development, EfD, DPS, 08-22.

MoFED (2010). *Growth and Transformation Plan (GTP) I.* The Federal Democratic Republic of Ethiopia, volume, 1: Addis Ababa: Ministry of Finance and Economic Development.

MoFED (2013). *Annual progress Report of the GTP I (2013).* Addis Ababa: Ministry of Finance and Economic Development.

National Planning Commission (NPC) (2016). *Growth and Transformation Plan (GTP) II* (2015/16-2019/20). The Federal Democratic Republic of Ethiopia, volume, 1. Addis Ababa, Ethiopia.

Nhemachena, C. and R. Hassan (2007). Micro-level Analysis of Farmers Adaptation to Climate Change in Southern Africa. IFPRI, Discussion Paper, 714.

Nisrane, F., G. Berhane, S. Asrat, G. Getachew, A. S. Taffesse, and J. Hoddinott (2011). Sources of Inefficiency and Growth in Agricultural Output in Subsistence Agriculture: A Stochastic Frontier Analysis, ESSP II Working Paper 19. AA: IFPRI.

Nyoro, J. K. and T. S.Jayne (1999). *Trends in regional agricultural productivity in Kenya.* Kenya Agricultural Marketing and Policy Analysis Project. Kenya Agricultural Research Institute and Michigan State University.

Oxford Poverty and Human Development Initiative (OPHDI) (2017). *Ethiopia Country Briefing, Multidimensional Poverty Index Data Bank*. OPHDI, University of Oxford.

Padgham, J. (2009). *Agricultural development under climate change: Opportunities and challenges for adaptation*. Washington DC: The World Bank.

Parikh, A. and K. Shah (1994). Measurement of Technical Efficiency in the North-West Frontier Province of Pakistan. *Journal of Agricultural Economics*, 45: 132-38.

Paul, E., Y. Nicholas, and J. Burnett (2013). *How will climate change spatially affect agriculture production in Ethiopia? Case studies of important cereal crops*. Springer: pp. 855–73.

Pitt, M. and L.F. Lee (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics*, 9: 43–64.

Rashidghalam, M., A. Heshmati, G. Dashti, and E. Pishbahar (2016). Comparison of Panel Data Models in estimating Technical Efficiency, IZA DP: 9807.

Reifschneider, D. and R. Stevenson (1991). Systematic departures from frontier: a framework for the analysis of firm inefficiency. *International Economic Review*, 32:715–23.

Reinhard, S., C.A.K. Lovell, and G.J. Thijssen (2002). Analysis of environmental efficiency variation. *American Journal of Agricultural Economics*, 84: 1054-65.

Schmidt, P. and R.C. Sickles (1984). Production frontier and panel data. *Journal of Business and Economic Statistics*, 2(4): 367–74.

Schultz, T.W. (1964). *Transforming Traditional Agriculture*. New Haven: Yale University Press.

Tafesse, G. (2003). Roles and externalities of agricultural growth to poverty reduction in Ethiopia. Unpublished report for THE FAOROA project, Rome, Italy.

Tesfaye, A. (2006). *The analysis of Urban Poverty in Ethiopia.* Australia: University of Sydney.

The World Bank (2013). *Doing Business 2013, World Bank 2013 report*. Washington DC: The World Bank.

The World Bank (2017). World Bank in Ethiopia: *Country's Economic Overview*. Washington DC: The World Bank.

Tirado, R., and J. Cotter (2010). *Ecological Farming: Drought-resistant Agriculture*. Green peace Research Laboratories, University of Exeter, United Kingdom.

Tsionas, E.G. and S.C. Kumbhakar (2014). Firm Heterogeneity, Persistent and transient Technical Inefficiency: A generalized True Random Effects model. *Journal of Applied Econometrics*, 29: 110-32.

Umesh A., A. P. Nejadhashemi, and S. A. Woznicki (2015). Climate change and eastern Africa: a review of impact on major crops. *Food and Energy Security*, 4(2): 110–32.

United Nations Development Program (UNDP) (2014). *Human Development Report 2014*. NY.

United Nations Development Program (UNDP) (2001). *Human Development Report 2001*. NY.

UNDP (2015). United Nations Environment Program. Country Climate change Framework. Environment and Disaster Risk Management Portfolio: Ethiopia.

United Nations World Population Review (2017). United Nations, Department of Economic and Social Affairs, Population Division: 2017 World Population Review.

Vedenov, D., J. Houston, and G. Cardenas, (2007). Production Efficiency and Diversification in Mexican Coffee-Producing Districts. *Journal of Agricultural and Applied Economics, Vol. 35, No. 3: 749-763.*

Yohannes H. (2016). A Review on Relationship between Climate Change and Agriculture. *Journal of Earth Science and Climatic Change*, 7:335.

CHAPTER TWO

Determinants of Consumption Expenditure and Poverty Dynamics in Urban Ethiopia[1]

Abstract

This essay analyzes the determinants of consumption expenditure and poverty dynamics in urban Ethiopia using panel data. It uses consumption expenditure to measure the poverty level and uses the fixed-effects model (FEM) and quantile regressions (QR) to investigate the determinants of consumption expenditure at mean and different quartiles and the MNL model to assess the determinants of chronic and transient poverty. In addition, it uses the Foster-Greer-Thorbecke indices to measure the intensity of poverty and employs both components and Spells approaches to decompose poverty into categories. The findings show that while a large number of households frequently moved in and out of poverty between the panel periods, many did not move far above the poverty line and remained vulnerable to falling back into poverty. Poverty indices show that poverty incidence, depth and severity consistently declined overtime. The Spells approach measurement indicates that more than 8 per cent of the households were trapped in chronic poverty while 56 per cent were affected by transient poverty. The FEM and QR results confirm that gender and age; primary, secondary and tertiary education; employment of the household head; remittances; and household locations are important determinants of a household's expenditure. MNL's results reveal that a female headed household was positively significantly associated with both chronic and transient poverty. Primary, secondary and tertiary schooling and employment of the household head and remittances and location of residence all significantly reduced chronic and transient poverty. Household size, dependency-ratio and casual-worker aggravated poverty categories. Age showed a positive effect on chronic poverty while it showed the opposite effect on transient poverty. These findings are important and can be used for initiating policy options to reduce poverty based on the assumption that any policy which is good for welfare improvement will also be good for poverty reduction. Policies that encourage remittances, smaller household sizes and improving access to education and employment activities will exert a positive effect on consumption expenditure and thus help in reducing urban poverty. The same set of households and household heads' characteristics are also important to alleviate either of the poverty categories or in charting out poverty reduction strategies.

Keywords: Consumption expenditure, quantile regression, poverty dynamics, panel data, urban Ethiopia.

JEL Classification: D13; C31; C33; C35; O15; O18; P46.

[1]An earlier version of this chapter was published in A. Heshmati (ed.) (2016).*Poverty and Well-Being in East Africa: A Multi-faceted Economic Approach*. Switzerland: Springer. Comments and suggestions from Giannis Karagiannis and Pär Sjölander on an earlier version of this paper are gratefully acknowledged.

1. Introduction

Poverty is a pervasive world reality which has become one of the greatest challenges of the 21st century. It is a key issue in the development arena that has received the attention of various agencies. Poverty is generally considered to be a situation in which the underprivileged do not have sufficient food and shelter, lack access to education and health services and find themselves in a state of unemployment, vulnerability and powerlessness. Poverty is multidimensional and so has to be looked at through a variety of indicators such as level of income and consumption, social indicators and indicators of vulnerability to risks, socio-political access and participation. Ethiopia is a densely populated agrarian economy in Africa. The country has achieved creditable development results over the past decade, as its economy grew at an average of 10.7 per cent (the World Bank, 2013). The country's Human Development Index (HDI) increased significantly over the past decade, rising from 0.284 in 2000 to 0.429 in 2012 and 0.435 in 2013 (HDR, 2014) showing an annual increase of about 3.34 per cent. Urbanization is growing at a fast rate in Ethiopia: 4.3 per cent (2006) and 3.57 per cent (2010-13), while the country's population is growing by 2.89 per cent (2014). Ethiopian urban population of 12 million (CSA, 2007) or 16 per cent of the total population, is projected to grow to 17.8million by 2015 and 22million by 2020. Recent official estimates show that poverty levels have declined sharply -- from 47 to 39 per cent between 1995 to 2005in rural areas -- while the country's poverty figures declined from 38.6 per cent in 2005 to 29.2 per cent in 2010 and to 28.7 per cent in 2011-12. In contrast, there has been an increase in urban poverty as there has been an increase in the incidence of poverty in urban areas from 33 per cent to 35 per cent between 1995 and 2005.

Hence, urban growth has been combined with a high prevalence of urban poverty. Studies also show that there is high poverty in urban areas. All this suggests a rapidly growing number of urban poor in the country. While sustained growth is central to development in countries such as Ethiopia, the possibility that poverty spells caused by short-lived shocks may persist are a matter of concern. Given this situation, the government has been pursuing urban development strategies through its Growth and Transformation Plan (MoFED, 2010) to build on the success of its former plan PASDEP for eradicating poverty. However, as in most other developing countries (DCs), poverty reduction strategies and policies in Ethiopia too are primarily informed by periodic cross-sectional data that provides estimates of poverty. Interestingly, the focus of poverty reduction strategies and policies drawn from such studies are likely to address chronic poverty—poverty that is not necessarily reflected in cross-sectional data, rather than reflecting short-term poverty spells that are caused by short-lived shocks.

Thus, while estimates of poverty at specific points in time might correlate with chronic poverty to some extent, short-run poverty reduction strategies require more representative estimates as such spells of poverty are transient in nature. Further, as argued by Haddad and Ahmed (2003) transient poverty which is a result of short-term shocks is likely to be temporary and so reflects the vulnerability of the non-poor. This in turn magnifies the limitations of poverty reduction strategies that focus only on poverty in the long-run and not on poverty in the short term. These strategies fail to protect vulnerable households from falling into poverty. Moreover, it is widely noted in literature that different policies have different implications for transient and chronic poverty (Jalan and Ravallion, 2000).Hence, an issue of interest is identifying the extent to which there is an overlap between the factors that explain transient and chronic poverty. If the determinants of chronic and transient poverty are different, then different policy measures are required to address these two aspects.

Most previous studies on consumption poverty in Ethiopia have focused on rural areas (Dercon, 2004; Dercon et al., 2005). Though important, the results and insights generated by most of these studies did not necessarily in the circumstances of urban residences. Further, there are relatively few studies on the poverty dynamics in urban Ethiopia; urban poverty has been given less attention in research and little quantitative work has been done to explain the determinants of poverty, particularly using panel data. Tesfaye (2006) analyzed urban poverty using the Ethiopian Urban Households Survey (EUHS) data collected in 1994 and 2000. His results show that the incidence of urban poverty was high with a PHCI of 41 per cent in 1994 and 43 per cent in 2000. His results of the decomposition of poverty into growth and inequality effects confirmed that both growth and re-distribution were useful instruments in combating poverty. Further, an examination of the association between different socioeconomic characteristics and poverty revealed that households consisting of casual workers and female heads engaged in business activities were relatively poor. Conversely, households where the head had completed tertiary education suffered from the least incidence of poverty. Alem et al., (2014) used EUHS's panel data to investigate the persistence and correlates of subjective and consumption poverty in urban Ethiopia. Their dynamic-Probit regression results showed that households with a history of poverty continued to perceive themselves as poor even if their material consumption improved. The authors reported that despite a decline in consumption poverty in recent years, subjective poverty had remained largely unchanged.

However, as per my knowledge only a few studies focus on analyzing the determinants of chronic and transient poverty and thus an analysis of the determinants of poverty transitions is overdue in urban Ethiopia. Given these gaps and growing poverty incidence in urban areas, it is important to assess and investigate the determinants of consumption expenditure and identify the factors that explain poverty transitions/dynamics in urban Ethiopia. Consequently, this essay analyzes households' consumption expenditure and poverty dynamics in urban Ethiopia using panel data. It pays specific attention to investigating the factors affecting consumption expenditure and determinants of chronic and transient poverty that are mostly related to demographic, human capital and socioeconomic characteristics of households.

Methodologically, the study uses consumption expenditure to measure poverty levels; it also decomposes poverty into categories in urban Ethiopia. Hence, in addition to econometric models, the study also uses the Foster-Greer-Thorbecke (FGT) indices to measure poverty and uses both component and Spells approach to decompose poverty into chronic and transient. For the econometric analysis, the study used two groups of econometric analyses in two parts. In the first, it looked at the determinants of per capita consumption expenditure (PCCE) using the fixed effect model (FEM) and supplemented it by a semi-parametric conditional quantile regression (QR) at different quartiles. In the second part, it explored determinants of chronic and transient poverty using a categorical multinomial logistic regression (MNL) model using panel data. The two methods/parts are distinct but complementary in an analysis of expenditure and poverty and its dynamics. The first (the consumption models) shed light on the key determinants of consumption expenditure or consumption poverty, while the second (the MNL model)provides a picture of poverty categories which help identify target groups to which the government can direct its poverty alleviation strategies. Together with the MNL model, the three methods allow the identification of the poor and their decomposition into poverty categories; they also allow their separation from the non-poor segments of the population. Identifying and estimating the effects of the determinants of household expenditure and poverty categories and their effective use in policy design and implementation suggest the presence of direct relationships between the three methodologies and their complementarities.

This essay contributes to poverty literature in a number of ways. First, it investigates the welfare/PCCE movement and poverty dynamics of urban households over time using standard poverty measures and poverty decomposition methods into transient and chronic poverty status. The study contributes to poverty literature because of way in which it analyzes poverty by employing alternative econometrics techniques to corroborate the results by compensating for their limitations and also their complementarities. Lastly, by filling these gaps, it contributes to urban poverty literature in Ethiopia by providing evidence on relevant correlates of both PCCE and poverty both from household head's characteristics and household characteristics.

The remainder of the essay is organized as follows. Section 2 provides a brief relevant theoretical and empirical literature review on poverty. Section 3 provides the methodological approach and the dataset used. Section 4 gives a descriptive analysis and regression estimates and discusses the empirical findings of the study. Section 5 gives the conclusions and policy implications of the study.

2. A Brief Review of Literature

2.1 Theoretical Literature

Poverty is a relative concept that can change over time and space. In its most basic form poverty can be defined as deprivation of well-being which has been a concern for policymakers. According to UN-HDR, approximately 1.2 billion people worldwide earned US$ 1 a day in 2000; 2.4 billion were without basic sanitation; one billion were illiterate; 100 million were homeless; and approximately 100million children lived on the streets (UNDP, 2000). The ramifications of poverty extend far beyond just the problems associated with a lack of income. Poverty affects many aspects of the human condition like economic, social, physical, moral and psychological. As a result, different approaches are followed for the conceptualization of poverty. The traditional approach to poverty usually links it to the deprivation of income or consumption. One modern approach is the ‘welfarist’ and the ‘non-welfarist’ approach. The former defines the concept of well-being on the basis of the link that exists between income and utility/standard of living, while the latter has little focus on utility. Following either of the two, different individuals and institutions have defined poverty differently. Sen (1976) relates poverty to entitlement failures to various goods and services. And as per the World Bank (1996) poverty is being unable to meet ‘basic-needs’ including food, health, education and shelter. Hence, it defines poverty as the inability to attain a minimal standard of living and perceives poverty as a multidimensional concept including deprivation. Economists, however, often prefer to view the concept of well-being in terms of the ‘welfarist’ approach. They take expenditure on goods and services consumed by individuals valued at market prices to categorize a person as ‘poor’ or ‘non-poor’. This money-metric-utility is derived from the neoclassical consumer theory -- poverty is said to exist in a given society when people are unable to obtain minimum basic requirements necessary to sustain an individual’s life.

Another approach to defining poverty is to see societal well-being from the perspective of severity as ‘chronic’ and ‘transient’. Chronic poverty is defined as persistent socioeconomic deprivations, whereas transitory poverty is temporary deprivations (Jalan and Ravallion, 1998). The former is linked to a host of factors like lack of skills, lack of productive resources and socio-political and cultural factors. The latter is linked to natural and man-made disasters and is easily reversible.

In its multidimensional aspect, poverty is treated as an outcome of multidimensional factors that include not only income and calorie intake but also different social, economic and demographic factors. However, there are essentially three broad categories of the definitions of poverty -- absolute poverty, relative poverty and subjective poverty. Absolute poverty defines people as poor when some of their absolute needs are not sufficiently satisfied. In relative poverty, a person is poor if s/he has less than what others have. In subjective poverty, the identification of the poor and the non-poor depends on the subjective judgment of individuals on what constitutes a socially acceptable minimum standard of living in their society.

2.1.1 Measuring Poverty: The Poverty Line and Poverty Indices

Along with the evolution of the concept of poverty, the methods for measuring poverty too have been developed. Most strikingly, UNDP-HDR (2010) has developed the Multidimensional Poverty Index (MPI). MPI is a combination of the conventional and new approaches to measuring poverty which counts on three dimensions of poverty: living standards, health and education. Conventional methods are helpful if they are used in combination with later approaches. Poverty is measured by constructing a poverty line or/and computing poverty indices.

The poverty line is basically defined as a certain amount of money spent by a person per day to buy basic goods and services to live without material deprivations. However, the definition of a poverty line depends on how one understands the concept of poverty. Hence, it varies across individuals, households, societies, etc. due to a number of factors including differences in taste, preferences and prices. The international poverty line was originally initiated by the World Bank and was set out at US$1 per day-per person in 1985 PPP prices. It was then updated to US$1.08 per person-per day in1993 PPP prices. The World Bank then set the international poverty line as US$1 a day (lower poverty line) and US$2 a day (upper poverty line). Poverty lines are, however, subject to a number of constraints and criticisms. Consequently, for the sake of convenience, each nation has had its own set of poverty lines, called country specific poverty lines.

Definitions of poverty line belong to the three main categories of poverty definitions given earlier. Based on the definition of absolute poverty, there are different methods for defining the absolute poverty line. The most common method of constructing the absolute poverty line is the CBN approach. According to Ravallion and Bidani (1994) CBN defines absolute minimum requirements in terms of basic needs such as food, clothing, housing, healthcare and education. Another method of defining an absolute poverty line is the FEI approach under which a poverty line is set by computing the level of consumption/income at which households are expected to satisfy the normative nutritional requirement of 2,200 Kcal per adult per month (Greer and Thorbecke, 1986).

Based on the definition of relative poverty the relative poverty line is the fraction of mean or median income or percentile of the income/expenditure distribution technique. It is set either at one-half, one-third or two-third of the mean/median income or percentile of the income distribution. Depending on the proportion chosen by the investigator/researcher, the percentile of expenditure distribution involves categorization of the population into different level of quartiles. Lastly, the population in the lowest or two quartiles from the bottom can be considered as poor, which is decided by the investigator himself with the corresponding cut off income level as the relative poverty line. Unlike these approaches, in the definition of subjective poverty, the subjective poverty line depends directly on the opinions and feelings of concerned individuals to determine the minimum level of income for themselves.

After constructing the poverty line based on one of these approaches, the poverty indices are computed. The most widely used poverty measure using an index is the Foster-Greer-Thorbecke poverty index measurement, known as the FGT index that belongs to the 1984 class (Foster et al., 1984). The FGT index measurement measures poverty through three indices: the poverty headcount index (PHCI), the poverty gap index (PGI) and the squared poverty gap index (SPGI). The HCI measure of poverty is simply the ratio of the number of poor to the total population; PGI measures the average gap of the minimum standard of living which the poor are lacking; and SPGI measures the intensity of poverty by squaring the transfers needed so that very poor households are given a large weight (Dercon and Krishnan, 1998).

2.1.2 Decomposing Poverty

To analyze the determinants of poverty, we first determine the level of poverty and disaggregate it into its components. One popular approach for measuring poverty is that of Jalan and Ravallion (1998), where inter-temporal poverty is decomposed into long-term(chronic) and short-term (transient) poverty components/categories. Twoapproachesare followed to decompose theminto chronic andtransientpoverty categories-- the 'Spells' and 'component' approaches (Gleww and Gibson, 2006). The Spells approach (Baulch and McCulloch, 2003) is based on poverty spells experienced by an individual over a given period of time. The chronically poor are identified by the number or length of poverty spells that they experience so that all poor households are classified as either chronic or transient. According to this approach an individual is identified as chronically poor if her/his welfare or consumption is below the poverty line all the timeand s/he is identified as transiently poor if her/his welfare/consumption level is below the poverty line only sometimes. The demerit of this approach is that it focuses on the headcount measure of poverty which is not sensitive to the depth and severity of poverty. Further, it is sensitive to the frequency of the survey waves that are available (Gleww and Gibson, 2006). It is less likely to identify a household as always poor, for example, in 10 survey waves more than two or three of them since it is more likely for several reasons that a positive windfall may visit a household in 10 waves than in two or three waves.

The component approach of decomposing poverty is based on expected poverty overtime. According to Jalan and Ravallion (1998), the component approach defines transient poverty as the contribution of consumption variability to expected consumption poverty over time, with what remains being the measure of chronic poverty. In this approach, transient poverty is defined as the portion of expected poverty over time due to consumption variability while the chronic part is the portion of expected poverty overtime due to consumption when inter-temporal variability of the consumption has been smoothed out. Hence, according to this approach a household is chronically poor if its time-mean consumption is below the poverty line and transiently poor if its time-mean consumption is above the poverty line but one of its consumption levels is below the poverty line.

2.2. Review of Empirical Literature

A considerable number of studies on measuring poverty and its determinants have been conducted in developing countries (DCs). In what follows, I review these studies focusing on DCs in general and on studies on Ethiopia in particular, though there are very few urban poverty studies on the country.

2.2.1 Level and Determinants of Poverty in Developing Countries

Relatively little research on poverty dynamics has been undertaken in developing countries, and specifically in SSA, mainly due to lack of longitudinal data that collects relevant information from individuals and households. However, there are a few exceptions. Jalan and Ravallion

(2000) studied poverty dynamics in south-west rural China. They used data on 5,854 households over 1985–90 to test whether transient poverty was determined similarly to chronic poverty. They defined chronic poverty as having time-mean consumption below the poverty line. Households experienced transient poverty if they had been observed to be poor at least once in the available data and had time-mean consumption above the poverty line. Using quintile regression, the authors found that a household's stage of life cycle, physical wealth and cultivated land were the most important variables for transient poverty. Demographic characteristics, education, household members' employment status, physical wealth and cultivated land were more important for chronic poverty. Tong (2011) analyzed the key determinants of chronic and transient poverty using an econometric approach in Cambodia from three-period panel data of 827 households. He measured welfare by both real consumption per capita and a wealth index (which was estimated by a principal component analysis). Households that had a wealth index below the 39th percentile of the wealth index (cut-off line) in all three years were defined as chronic poor while the transient poor were those with a wealth index below the cut-off line for at least one period. The study found that the transient poor accounted for more than 75 percent of the total poor households.

Mok et al., (2007) studied determinants of urban household poverty in Malaysia using a logistic regression. They used a sample of 2,403 urban households from the 2004-05 expenditure survey. Their study concluded that human capital significantly reduced the chances of being poor while migrant workers were more prone to poverty. It also found household size, race and regions as important determinants of poverty in urban Malaysia. Olaniyan (2000) examined the role of household endowments in determining poverty in Nigeria using panel data from the national consumer survey. He employed the Probit model for three periods and found that household endowments were significant determinants of poverty among both rural and urban households. In their analysis of determinants of regional poverty in Uganda, Nathan et al., (2002) applied the FEI methodology and logistic regression to analyze key determinants of poverty. They reported that educational levels of household heads, household size and migration status were significant determinants of poverty at multivariate levels. Haddad and Ahmed (2003) applied quintile regression to two-period panel data of 347 households in Egypt to identify the causes of chronic and transient poverty. They found that household size, number of members aged less than 15 years, age of household head, livestock assets, agricultural land, education level of household members and their employment status affected chronic poverty. Only members aged over 60 years and agricultural land increased the likelihood of transient poverty.

2.2.2 Level and Determinants of Poverty in Ethiopia

Several empirical studies have examined the nature and determinants of poverty in Ethiopia (see, for example, Bigsten and Shimeles, 2008; Dercon, 2004; Dercon and Tadesse 1999; Dercon et al., 2005; Jayamohan and Amenu, 2014; Kedir and McKay, 2005). However, most of these focus on rural areas. While important, the results and insights generated by such studies do not necessarily carry over to the urban context. There are obvious differences in poverty context and its correlates in rural and urban areas. Dercon and Tadesse (1999) calculated indices of both urban and rural poverty in Ethiopia based on the basic needs approach of poverty line construction and found that the incidence, depth and severity of rural poverty in Ethiopia was 31, 11 and 5 per cent respectively while that of urban poverty was 40, 16 and 9 per cent respectively.

There are also obvious differences in rural and urban poverty correlates such as differences in household head's characteristics and household's characteristics. For example, Alem (2014) used a EUHS panel dataset to investigate the persistence of poverty in urban Ethiopia with a particular focus on the role of intra-household heterogeneity in occupations. He also investigated the effects of international remittances, which have become an important component of urban households' incomes over the last decade by employing a dynamic Probit and system GMM. His regression results indicate that international remittances and labor market status of non-head household members were important determinants of households' poverty status.

Relatively few earlier studies have attempted to assess poverty and its associated factors in urban Ethiopia. Kedir and McKay (2005) analyzed urban chronic poverty based on quantitative evidence using EUHS panel data for 1994-97. They used real total household expenditure per month as the welfare indicator. Their results indicate that high-level chronic poverty (25.9 per cent) was more concentrated in central and northern cities. Households that experienced transitory poverty constituted 23 per cent of the total households. They did further quantitative analyses supported by a subjective evaluation of welfare changes and showed the congruence between subjective responses based on income and quantitative approaches through consumption expenditure. Focusing on the persistence of poverty in both urban and rural Ethiopia, Bigsten and Shimeles (2008) used the Spells approach which involves estimating two hazard rates: one for the probability of exiting poverty at successive durations of poverty spells and another for the probability of re-entering poverty at successive durations of the non-poverty spell. Since their main purpose was investigating the dynamics of poverty in both urban and rural Ethiopia, they did not investigate other important variables that played a role in the dynamics of poverty in the context of urban areas including remittances from foreign sources, different levels of education, labor market participation and characteristics of other household members.

Kedir and Disney (2004) analyzed prices for measuring food poverty in urban Ethiopia using the 1994 EUHS data. They investigated the sensitivity of food poverty estimates to the choice of spatial price deflators and examined the determinants of household welfare and food poverty using OLS, binary and quintile regression techniques. They reported household composition, location, labor, market status, asset ownership and level of schooling as important determinants of poverty. Methodologically most of these studies used the class of decomposable poverty measures of FGT in measuring poverty. They decomposed poverty using either the Spells or component approach. For an analysis of factors associated with total poverty, chronic poverty and transient poverty different authors have used different econometric models such as multinomial logistic, Probit, and bi-variate Probit or Tobit models while others have employed quantile regression techniques.

3. Methodology and Dataset

3.1. Approaches to Measuring Households' Welfare Levels

My research employs mixed research methods to enrich its aim of identifying factors associated with escaping consumption poverty or otherwise and determinants of poverty dynamics. It uses per capita consumption to measure households' welfare levels; although households' per capita incomes can also be used for this but the consumption measure better captures the long-run welfare level than income. It also better reflects households' abilities to meet their basic needs. Moreover, PCCE in an adult equivalence unit better captures the consumption smoothing behavior of households and is thus preferred as a better indicator of welfare (Haughton and Khandker, 2009). It is also less susceptible to measurement errors, especially in the context of DCs. Accordingly, I computed aggregate households' PCCE applying the FEI methodology and the CBN approach. Then the aggregate PCCE was converted into adult equivalences to adjust for household size and composition using the method proposed by Dercon and Krishnan (1998).

3.2. Ways to Determine Households' Poverty Status and its Decomposition

After obtaining an aggregate PCCE in adult equivalence, the next step was performing the identification and aggregation exercises to determine households' consumption poverty status and for decomposing poverty into components. This identification itemized the poor and the non-poor, while the aggregation enabled a combination of information about poverty in an index. Identification of the poor is generally based on some poverty line that marks a limit to the welfare indicator. In my research, the incidence of poverty was estimated by using the relative poverty line which was set at the threshold of two-third of the median PCCE. A household was considered consumption poor if its PCCE in an adult equivalent unit was below the poverty line in the initial period, otherwise it was considered non-poor.

Poverty Indices and Decomposition

Next, I applied the most widely used poverty measures (for their consistency and additively decomposable nature (Foster et al., 1984) and also suggested by Kakwani and Silber (2008) to look at the poverty aggregation or indices for the urban poor. This is known as the FGT index which belongs to the 1984 class.

The FGT poverty index is given as:

$$(1) \qquad P_\alpha = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^\alpha = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{G_i}{z}\right)^\alpha$$

where, y_i is PCCE in an adult equivalent unit for individual i; z is the poverty line; $G_i = z - y_i$ is the poverty gap; q is the number of people in the sample whose PCCE is below the poverty line; N is the size of the sample in the study population;and αis the poverty aversion parameter that takes values of zero, one or two. Moreover, Jayamohan and Amenu (2014) have pointed out that the FGT index has received wide acceptance because it has most of the desirable properties. Moreover they have argued that the poverty measure, P_a, satisfies the monotonicity axiom for a > 0, the transfer axiom for a > 1 and the transfer sensitivity axiom for a > 2. Hence, by using the FGT index, one can estimate three aspects of poverty -- incidence, depth and severity.

By setting the value of α at zero, one and two respectively, the FGT poverty measure formula delivers a set of povertyindices: PHCI, PGI and SPGI respectively. When α is larger, the index puts more weight on the position of the poorest. Equation 1 represents the three FGT poverty indices, that is, setting α equal to zero, P_α becomes P_0 -- the poverty headcount index (PHCI) which measures the incidence of poverty or the proportion of the population living below the poverty line. Although it is easy to interpret, PHCI is not sensitive to how far below the poverty line the poor people are, that is, it does not indicate how poor the poor are. When α equals to one, P_α becomes P_1-- the poverty gap index (PGI) which measures the depth of poverty or extent to which individuals fall below the poverty line as a proportion of the poverty line but ignores its severity. It measures the average poverty gap, showing the shortfall in a poor person's expenditure from the poverty line expressed as an average of all people in the population. It can be used as an indicator of the minimum cost of eliminating poverty through targeted transfers. Setting α equal to two, P_α becomes P_2 -- the squared poverty gap (poverty severity) index (SPGI) that averages the squares of the poverty gaps relative to the poverty line measuring the severity of poverty. At P_2, the weight given to each of the poor is more than proportional to the shortfall from the poverty line.

I also used the inter-temporal poverty measure and decomposition approaches: the 'Spells' approach and the 'component' approach, to decompose poverty into its chronic and transient dimensions. As discussed in literature (Haddad and Ahmed 2003; Kedir and McKay 2005), long-term poverty is called 'chronic poverty' and poverty resulting from consumption/income shocks that are likely to be temporary is called 'transient poverty'. Transient poverty reflects the vulnerability of the non-poor.

Building on Baulch and McCulloch (2003) and Gleww and Gibson (2006), for the Spells approach, I propose a 6-tier system for the study:

- Always poor: Welfare/PCCE in each period/years below the poverty line;
- One period poor: Welfare/PCCE falls below the poverty line in one of the years;
- Two period poor: Welfare/PCCE falls below the poverty line in two of the years;
- Three period poor: Welfare/PCCE falls below the poverty line in three of the years;
- Four period poor: Welfare/PCCE falls below the poverty line in four of the years;
- Never poor: Welfare/PCCE in all periods above the poverty line.

These poverty categories can be further aggregated into the chronically poor and the transiently poor groups based on the frequency of the households being poor and the never-poor group otherwise.

Component Approach's Poverty Indices and Decomposition

Following Jalan and Ravallion (2000), let $y_{i1}, y_{i2}, \ldots, y_{iT}$ be a household's consumption stream over time T dates; and p is some well-defined poverty measure, which is an agreed measure of household welfare that is adjusted for economies of scale and prices such as those in the FGT poverty measures.

The inter-temporal aggregate measure of poverty of household i: that is the expectation over time of the poverty measure at time, $\mathbf{p}_i$ is given by:

$P_i = \frac{1}{T}\sum_{t=1}^{T} P_{it}$; where P_{it} is: $p_{it} = \begin{cases} \left(\frac{z - y_{it}}{z}\right)^{\alpha} & if \ \ y_{it} < z \\ 0 & if \ \ y_{it} \geq z \end{cases}$; z is the poverty line.

Then, the inter-temporal poverty index is given as:

$$P_i = P(y_{it}) = \frac{1}{T}\sum_{t=1}^{T} P_{\alpha} \ = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{N}\sum_{i=1}^{q}\left(\frac{z - y_{it}}{z}\right)^{\alpha}\right)$$

All notations remain the same as they are in Equation 1.

The chronic component of poverty is defined as:

$$(2) \qquad p_i^c = \begin{cases} \left(\frac{z - y_i}{z}\right)^{\alpha} & if \ \ y_i^* < z \\ 0 & if \ \ y_i^* \geq z \end{cases}$$

where, y_i^* is the inter-temporal mean consumption expenditure of household i.

Equation 2 can be re-written as the expectation over time of a household's chronic poverty at each point in time p_{it}^c, but since the household's chronic poverty does not change over time $p_i^c = p_{it}^c$. Hence the chronic component measure of the poverty indexis given as:

$$(3) \qquad p_i^c = p_{it}^c = P(y_{it}) = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z - Ey_{it}}{z}\right)^{\alpha} \ ;$$

where, Ey_{it} is the expected value of consumption for the i^{th} household and q is the number of chronic poor. Here the time mean consumption, y_i^*, is as sumed to be equivalent to the expected value of consumption, Ey_{it}.

The transient component is obtained by taking the difference between inter-temporal and chronic poverty. The transient component $P_i^T(y_i)$ of P (.) is the portion that is attributable to inter-temporal variability in consumption and is given by netting out the chronic component from the aggregate measure:

$$(4) \qquad P_i^T = P_i - P_i^c = P(y_{it}) - P(Ey_{it})$$

Further, as per the component approach a household was characterized as chronically poor when its time-mean consumption was below the poverty line and transiently poor if its time-mean consumption was above the poverty line but one of its consumption levels was below the poverty line and never poor otherwise.

3.3. Model Specification and Estimation

One of the primary concerns of researchers while analyzing poverty dynamics is the adoption of an appropriate model -- whether to treat poverty status and transitions as changes in a continuous welfare measure or as a discrete variable. In recent poverty literature, the most widespread regression techniques used for identifying factors that contribute to poverty and analyzing poverty dynamics are divided into two main categories (Haughton and Khandker, 2009). The first involves modeling welfare indicators or their change directly to explain the level of PCCE as a function of explanatory variables which are considered as causes of poverty that are typically individual household-level characteristics.

The second method explains whether a household is poor or not by using poverty functions such as the binary Probit/logit regression in which the explanatory variables are the same as in the first type but the dependent-variable is binary. These poverty analyses are useful when the underlying dependent variable of interest is unobservable. They are, however, often criticized for introducing measurement errors by using arbitrarily defined poverty lines. Moreover, the second method is subject to criticism as the loss of information in converting a continuous variable is seen as its key limitation, that is, information on whether a household is poor or not is known, but more information such as how poor the household is (which is given by PCCE) is lost due to counting on a poverty line. However, Baulch (2011) as cited by Alem 2014, has argued that while one does either a discrete or a continuous variable based analysis of poverty it is difficult to claim that one is better than the other as each approach has its own advantages and limitations depending on the data available and the research problem that one is interested in. He also notes that the adoption of an appropriate model usually depends on the primary purpose of the study.

Accordingly, this research used a model adopted from a typical poverty model suggested by Haughton and Khandker (2009) in the World Bank's *Handbook of Poverty Analysis* which has been widely used in poverty studies (Engvall and Kokko, 2007; Shinkai, 2006). It uses two types of regression techniques. Econometrically, my study used two groups of econometric analyses in two parts: in the first, it looked at the factors that contribute to poverty proxied by the logarithm of per capita consumption expenditure (PCCE) through fixed effect and conditional quantile regression models at mean and different quartiles (Dercon, 2004). In the second part, it explored the determinants of chronic and transient poverty using a categorical multinomial logistic regression (MNL). The two methods/parts are distinct but complementary in an analysis of expenditure and poverty and its dynamics. The first (consumption models) shed light on the key determinants of consumption poverty while the second (the MNL model) provides a picture of poverty which helps identify target groups to which the government can direct its poverty alleviation strategies.

The rationale for using quantile regression (QR) is that it provides a more complete description of the underlying conditional distribution compared to other mean-based estimators. Moreover, in contrast to the mean-based approach (for example, OLS), the QR procedure is arguably less sensitive to outliers and provides a more robust estimator in the face of departures from normality. Also, QR has robust properties in the presence of heteroscedasticity and it makes no assumption about the distribution of the error in the model (Koenker and Bassett, 1978) and is invariant to monotonic transformations such as log (.).

However, one limitation of such a level regression is that it does not provide probabilistic statements about poverty status and assumes that consumption is negatively associated with poverty at all consumption expenditure levels. Hence, such regressions (FEM and QR) need to be complemented by other techniques like a categorical (multinomial logistic, MNL) regression model.

As discussed earlier the rationale for using MNL regression is that the first types of regressions can only identify factors which affect PCCE but they cannot explain why some households are always or sometimes or never poor. Hence, it is important to distinguish chronic poverty from transient poverty in the sense that moving into and out of poverty looks less serious than remaining in poverty. Someone who is poor now, but can reasonably expect to be out of poverty next year is in a better position than someone who is equivalently poor now and who is likely to remain poor in the future. Thus, it is reasonable to view poverty categories as a nominal variable and use the second type of regression model to investigate the factors affecting either of the poverty categories by taking advantage of a logistic regression. Accordingly, using the Spells approach poverty measurement, we run a multinomial logistic (MNL) regression model to examine the factors affecting the likelihood of a household being in either of the poverty groups. The dependent variable for the MNL regression takes the value of zero, one and two for never poor, transiently poor and chronically (or always) poor.

3.3.1 Models' Specifications

Consumption Models: Fixed Effect and Quantile Regressions

This part of the essay uses robust standard fixed-effects model and conditional quantile regressions to estimate the effects of household characteristics on PCCE for urban residents at different parts of the distribution. The standard fixed-effects model enabled controlling for unobserved time-invariant characteristics of households to explore the effect of a set of independent variables on PCCE. The standard panel data model based on the human capital earnings function developed by Mincer (1994) is given as:

$$(5) \qquad \ln c_{it} = \ln PCCE_{it} = X_{it}\beta + \varepsilon_{it}$$

where, $\ln c_{it}$ *or* $\ln PCCE_{it}$ is the natural logarithm of the per capita expenditure in adult-equivalence for observation i, in period t; X is a vector of exogenous explanatory variables(of household head's characteristics and household characteristics (see Tables 1and 2 for the explanatory variables); β are vectors of parameters to be estimated; ε_{it} is the disturbance term; and $\varepsilon_{it} \sim N(0,\sigma_{\varepsilon}^{2})$. Hence, given the panel data model (5) a consumption model with a fixed effect estimator to detect determinants of household welfare (per capita consumption expenditure) is employed. Moreover, the model is specified as a non-linear regression function to capture any non-linear effects of covariates on the dependent variable.

The standard fixed effect model is given as:

$$(6) \qquad \ln PCCE_{it} = \ln c_{it} = \alpha + \beta X_{it} + \eta_i + \varepsilon_{it}$$

where, η_i is a household's fixed effects that capture unobserved time-invariant household specific effects affecting PCCE; α is an intercept term. Other notations remain the same as they are in Equation 5.

In addition, we use the conditional QR introduced by Koenker and Bassett (1978) which allows one to look beyond the mean effects. The model is estimated at the conditional median as well as at other conditional percentiles. It therefore offers an opportunity for a complete view of the statistical landscape and the relationships among stochastic variables at different parts of the earnings distribution (see also Koenker, 2005).

Standard linear regression techniques summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function E(y/x).Analogous to the conditional mean function of linear regression we may consider the relationship between the regressors and the outcome using the conditional median function $Q_{\tau}(y/x)$, where the median is the 50^{th} percentile, or quantile τ, of the empirical distribution. That is, a conditional QR is a method of estimating conditional median functions in which one can use an optimization of a piece-wise linear objective function of residuals.

Equation 5 under conditional QR is specified as:

$$(7) \qquad Q_{\tau}\ln(PCCE_i \mid X_i) = X'_i\,\beta_{\tau} + \varepsilon_{i,\tau}$$

where, Q_τ represents the Mincerian model at the τ-th quantile of the distribution of PCCE conditional on the value of X; and β_τ is the estimated parameter for each variable correspondingly. Other notations remain the same as they are in Equation 5. Assuming that the τ-th quantile of error term conditional on the regressors is zero $(Q_\tau(u_{i,\tau}/x_i)=0)$ the τ-th conditional quantile of y_i with respect to x_i can be written as:

$$(8) \qquad Q_\tau(y_i/x_i) = \mathrm{x'_i}\,\beta_\tau$$

Using the median regression method, also known as the least-absolute-deviations (LAD) estimator, we minimize the sum of absolute residuals with symmetrical and asymmetrical weighting systems. The parameter vector β_τ can be estimated by:

$$(9) \qquad \hat{\beta}_\tau = \underset{\beta_\tau \in R^k}{\operatorname{argmin}} \left\{ \sum_{i:\, y_i \geq x'_i\,\beta_\tau}^{N} \tau \left| y_i - (x'_i\,\beta_\tau) \right| + \sum_{i:\, y_i < x'_i\,\beta_\tau}^{N} (1-\tau) \left| y_i - (x'_i\,\beta_\tau) \right| \right\}$$

$$= \underset{\beta_\tau \in R^k}{\operatorname{argmin}} \sum \rho_\tau (y_i - \xi(x_i, \beta_\tau))$$

For a QR analysis, we estimate the expenditure equation for different values of τ (10, 25, 50, 75 and 90 percent) for urban residents. The conditional quantile estimates potentially allows a more picture of the relationship between the conditional distribution of per capita consumption expenditure and the selected covariates. Moreover, these estimates allow a researcher to establish ceteris paribus the magnitudes of the effects of the covariates at different points of the conditional distribution on the entire distribution of ln (PCCE) in contrast to the conditional mean. Thus, it permits a chance of focusing on characteristics for poor households at lower quantiles and for the relatively rich households at upper quantiles. Common bootstrap methods such as the residual bootstrap and the paired bootstrap are described in Efron and Tibshirani (1994). Moreover, there are many types of bootstrapping (for example, wild bootstrapping, moving block bootstrapping and sieve bootstrapping).This essay considers the wild bootstrap for quantile regression estimators (Koenker and Bassett, 1978). I applied the pair-wise bootstrap re-sampling technique, since bootstrapping pairs are, in general, less sensitive to certain regularity conditions than bootstrapping residuals. In the pairs' bootstrap, instead of re-sampling the dependent variable, or residuals, possibly centered or rescaled, it bootstraps pairs consisting of an observation of the dependent variable along with the vector of explanatory variables for that same observation.

The Chronic-Transient Non-poor Model: A Multinomial logistic (MNL) Model

Using the Spells poverty measurement, this essay applied a multinomial logistic (MNL) regression model to examine the factors affecting the likelihood of a household being in either of the poverty groups. For this, I let the households' poverty categories, P_i be discrete variables taking values zero, one or two for never-poor, transient poor and chronically poor households respectively and depending on the covariates:

(10) $$P_i = \Phi_i X + \mu_i$$

Here X is the vector of covariates including demographic, human capital and occupational characteristics of the household, Φ_i -is vector of parameters and μ_i is the disturbance term.

In Equation 10, the discrete outcome variable P_i is defined as:

(11) $$P_i = \begin{cases} 0 \; if \; c_{it} \geq z \quad \forall t & Never \; poor \\ 1 \; if \; c_{it} < z \quad for \; some \; t & Transient \; poor \\ 2 \; if \; c_{it} < z \quad \forall t & Chronic \; poor \end{cases}$$

where, c_{it} is the inter-temporal per capita consumption expenditure at time t and z is the poverty line.

Hence, given the assumptions used earlier to describe the MNL model we wrote the conditional-probability (P_{ij}) that a household i is in a particular poverty state j and is modeled as a function of explanatory variables X_i as:

Let Y denote a random variable taking values $\{0,1,2,\}$, and let X denote a set of conditioning variables. Now ceteris paribus changes in the elements of X affect the response probabilities $P_{ij} = \Pr ob(Y_i = j|X_i)$ for $j = 0,1,2$. Since the probabilities must sum to unity, $\Pr ob(Y_i = j|X_i)$ is determined once we know the probabilities for j = 0, 1, 2.

(12) $$P_{ij} = \Pr ob(iPoverty = j|X_i) = \frac{e^{X_i^{'}\beta_j}}{\sum_{k=1}^{3} e^{X_i^{'}\beta_k}} \; and \; P_{ij} = \Pr ob(iPoverty = j|X_i) = \frac{e^{X_i^{'}\beta_j}}{1 + \sum_{k=1}^{2} e^{X_i^{'}\beta_k}} \quad for \; j = 0,1,2.$$

where, β_j represents a vector of coefficients in which β_0 is set to zero and j can take the values zero (non-poor), one (transiently poor) and two (chronically poor). The non-poor state (j = 0) is used as the base category in the regressions based on Equation 10. However, the parameter coefficients of the MNL model provide only the direction of the effect of the independent variables on the response variable; they neither represent the magnitude of change nor the probability. Hence, this requires estimating marginal effects or marginal probabilities of the explanatory variables given as:

(13) $$\frac{\partial P_j}{\partial x_k} = P_j \left(\beta_{jk} - \sum_{J=1}^{J-1} P_j \beta_{jk} \right)$$

The marginal effects measure the expected change in probability of a particular choice being made with respect to a unit change in an independent variable from the mean (Greene, 2007).

3.3.2 Estimation and Diagnosis

In a longitudinal/panel study it is common for some participants to drop out temporarily or permanently. If the drop-outs differ systematically from those who remain in the sample, the dataset is no longer representative of the original sample and the result of the remaining sample may be seriously affected by an attrition bias. However, if the attrition is not systematic, that is, there are no unique characteristics among those who drop out then there is no attrition bias although the sample decreases in size. To verify the differences between those who drop out andthose who remain in the sample, a number of tests have been proposed, including attrition probits (Fitzgerald et al., 1998) andpooling tests (Becketti et al. 1988). Alem and Soderbom (2012) checked for this on the same data using the two tests - one for attrition during 1994-2004 and another for 2004-09 and reported that attrition in the sample was less likely to bias the results from the sample of remaining households.

To address measurement errors and endogeneity this essay used PCCE as a preferred indicator of welfare as it better captures the consumption smoothing behavior of households and is also assumed to be less susceptible to measurement errors especially in the context of developing countries. For the specification test for the consumption model specification, we performed the Hausman-specification test (Wooldridge, 2002) to see if the unobserved fixed-effects were best treated as fixed or random effects so that we could use the best method. The test results showed fixed-effects as a more efficient model against random effects with a p-value of less than a 1 per cent significance level. Finally, to address concerns about the independence of irrelevant alternatives (IIA), we included an alternative specific constant to serve two purposes: firstly, to assure that the disturbance term has zero-mean and secondly it can mitigate and in some cases remove the inaccuracies due to independence from IIA.

3.4. Data, the Study Area and Variables

This study used five rounds of the Ethiopian Urban Socioeconomic Survey (EUHS),a household level survey panel data collected in 1994, 1997, 2000, 2004 and 2009. The first four waves were collected by the Department of Economics, Addis Ababa University (AAU) in collaboration with the Department of Economics, the University of Gothenburg and Michigan State University. It covered seven major cities–capitals Addis Ababa, Awassa, Bahir Dar, Dessie, Dire Dawa, Jimma and Mekelle, which were believed to represent major socioeconomic characteristics of the urban population in the country. A stratified sampling technique was used to include about 1,500 households which represented the urban population in which each city was represented in proportion to its population. Once the sample size for each city was set, the allocated sample size was distributed over all districts in each urban center. Households were then selected randomly from half of the kebeles in each district using the registration of residences available with urban administrative units.

The last round of the survey was conducted from the original sample by forming a sub-sample of the original sample covering four cities: Addis Ababa, Awassa, Dessie and Mekelle following a similar sampling strategy, comprising about half of the original sample. The sub-sample was checked and to see if it represented the major urban areas in the country as the original sample (Alem and Söderbom, 2012). Consequently, the analysis in this essay includes semi-balanced 566 panel households consisting of 2,630 observations over five rounds that were surveyed since 1994 in the seven cities. The dataset was comprehensive and addressed household living conditions including income, expenditure, demographics, educational status, occupation, production activities and other variables on household and individual levels.

Selection of Variables

The choice of study variables was guided both by economic theory and empirical observations for urban poverty in Ethiopia and in developing countries. Poverty studies in developing countries including those in Ethiopia have shown that demographic, human capital and socioeconomic characteristics of the household affected PCCE and poverty categories. However, the effect varied in time and space depending on specific situations in the study countries/areas, making it imperative to test their effects in urban Ethiopia. Accordingly, a continuous variable-PCCE in logarithm term was selected as the dependent variable for the fixed-effects model and the quantile regression. The discrete variable of poverty categories was used as the dependent variable for the MNL model using households' characteristics mostly related to the demographic, educational and socioeconomic characteristics as explanatory variables for both models.

The analysis includes household head's demographic characteristics such as age, gender and educational levels as well as household characteristics like family size, dependency ratio and other characteristics as the explanatory variables. These variables have direct and indirect influence on household consumption and hence on the extent of poverty at the household level. The educational characteristics include primary, secondary and tertiary school completion of household heads while the socioeconomic characteristics include employment status of household heads, a casual worker member and number of casual worker members in households, value of remittances received and location of residence. Similar variables have been used in previous studies in Ethiopia and in other developing countries.

There are claims that female-headed households receded into poverty more quickly than male-headed households because of the persistence of gender inequalities and women's physical limitations (Sengupta, 2007). Further, household size may have a negative relationship with household per capita consumption expenditure in developing countries (Lipton and Ravallion, 1994).There is also evidence indicating that family members have a positive relationship and result in raising the level of per capita consumption expenditure/income of a household, which is possible if members cooperate with each other and operate as individual households. The positive association between the per capita consumption expenditure level and household size can be due to sharing of fixed costs of running a household like rent, household appliances and utility bills. Further, larger households may be able to take advantage of bulk discounts with larger purchases (Meenakshi and Ray, 2002).

This essay hypothesizes that an increase in family size had a negative influence on PCCE and thus positively impacted poverty and poverty categories of the household. The dependency ratio, a variable indicating the ratio between the dependent parts usually includes all household members under the age of 15 years and those over 64 years while the productive part includes all household members between15 and 64 years. Hence, other things being equal, an increased dependency ratio is likely to place an extra burden on a household's PCCE leading in its decrease and it is generally expected to be positively related to both transient and chronic poverty (McCulloch and Baulch, 2000). It is generally held that education has a positive effect on earnings and thus on consumption levels and hence is expected to relate positively to PCCE but negatively to both poverty categories.

4. Empirical Results and Discussion

4.1. Descriptive Results

4.1.1. Descriptive Statistics of Households' Major Characteristics overtime

Tables 2.1 and 2.2 presents the summery statistics and evolution of PCCE, relative poverty and other major characteristics of households over the period 1994-2009.According to Table 2.1, PCCE's mean value in logarithm terms in the sample was about 4.51 in 1994 which rose steadily to 4.75 in 2009. This shows that PCCE had a modest increase over time. The research used age and age- squared to test whether there is a conventional concave relation between age and consumption expenditure. As can be observed from Table 2.1, the mean age of the sample households was 50 years with the minimum and maximum age being 25 and 97 years respectively. The mean of the sample households' size was 5.3 with a maximum size of 18 members. In 2009 mean of the family size was 4.36, which was lower than it was in1994, reflecting a natural process by which children exited the households as they became older. Consistent with this, the average number of children and number of elders in the households fell from 2.22 and 0.17 in 1994 to 0.99 and 0.06 in 2009 respectively.

As presented in Table 2.2, about 45 per cent were female-headed households (FHHs). There was also an increasing trend in FHHs while the converse was true in male-headed households (MHHs). The gap between them declined from 20 per cent in 1994 to almost nil in 2004 while the gap increased to 2 per cent more FHHs in the last wave of the data. From Table 2.2 one can also observe that a majority of the sample (70 per cent) had attended at least elementary school education out of which 42 per cent had completed primary schooling while 22 per cent had completed secondary education and only 6 per cent had completed tertiary level education.

Table 2.1 Summery Statistics of Continuous Variables Overtime (NT = 2,630)

	1994		1997		2000		2004		2009		Total	
Variables	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Ln PCCE	4.5	0.8	4.5	0.8	5.2	1.2	5.2	1.1	4.8	0.7	4.8	1.0
Head's age	47.9	13.3	47.1	13.5	49.9	13.5	51.5	13.6	55.7	14.6	50.0	13.9
Family-size	5.3	2.6	5.3	2.6	5.7	2.8	5.6	3.2	4.4	2.6	5.3	2.8
Number of children	2.2	1.8	2.4	1.8	1.8	1.6	1.6	1.5	1.0	1.1	1.9	1.7
Number of elderly	0.2	0.4	0.2	0.4	0.7	1.5	0.2	0.5	0.1	0.3	0.3	0.8
Dependency-ratio	0.6	0.3	0.6	0.3	0.6	0.3	0.5	0.3	0.6	0.3	0.6	0.3
Casual-worker-members #	0.1	0.4	0.1	0.4	0.1	0.5	0.2	0.5	0.2	0.6	0.2	0.4

Source: Author's calculations.

When we see the socioeconomic characteristics of the households, 48 per cent of urban household heads were reportedly employed. On the other hand, only about 9 per cent of the urban households reported to be casual workers. Moreover, 15 per cent of the urban households reported having casual workers ranging up to a maximum of 5 members per household.

Table 2.2 Summary Statistics (Percentage) for Dummy Variables Overtime (NT = 2,630)

Variables (0 =No, 1 =Yes)	1994	1997	2000	2004	2009	Total
Head's gender (female)	0.40	0.42	0.44	0.49	0.52	0.45
Head primary schooling-complete	0.46	0.46	0.38	0.37	0.45	0.42
Head secondary schooling-complete	0.19	0.19	0.36	0.21	0.12	0.22
Head tertiary schooling-complete	0.06	0.05	0.04	0.06	0.10	0.06
Head's employment	0.55	0.54	0.46	0.38	0.47	0.48
Casual-worker member	0.11	0.11	0.09	0.07	0.06	0.09
Received remittances	0.08	0.09	0.10	0.18	0.31	0.14
Poverty headcount & percentage	221(0.39)	215(0.38)	124(0.26)	114(0.22)	96(0.20)	770(0.29)

Source: Author's calculations.

The descriptive statistics show that 55 per cent of the urban households lived in Addis Ababa. Table 2.2 also shows the growing role of remittances in urban Ethiopia over the past 15 years. There was an increase in the number of households receiving remittances, as only 8 per cent households received remittances in 1994 which increased to 31 per cent in 2009. From Table 2.2 we can also see that there were 221 households who were below the poverty line (39 per cent) in 1994 which dropped to 124 (22.2 per cent) in 2000, then declined consistently and reached 96 (20 per cent) in 2009. This shows that there was high dynamism in moving in and out of poverty after falling into poverty in 1994 and that the persistence of poverty decreased steadily over the panel period.

4.1.2. Analysis of Poverty Measured by Poverty Indices (*Incidence, Depth and Severity*)

The computed FGT poverty indices complement the poverty analysis enabling a measurement of the intensity of poverty (its incidence, depth and severity). Table 2.3 shows the extent (incidence, depth and severity) of consumption poverty in urban Ethiopia using FGT measures in terms of PHCI, PGI and SPGI for 1994-2009. As shown in Table 2.3, the incidence of relative poverty was higher in the initial period which decreased in terms of prevalence, depth and severity during 1994-2009. It is interesting to note that the extent of average deprivation declined indicating that poor households were increasingly concentrated around the poverty line over time so that the burden of reducing poverty fell somewhat.

Table 2.3 FGT-Poverty Indices (NT = 2,630)

FGT-Indices	1994	1997	2000	2004	2009	Total
PHCI*(incidence)*	0.390	0.380	0.262	0.219	0.201	0.293
PGI (*depth)*	0.052	0.052	0.030	0.020	0.022	0.036
SPGI*(severity)*	0.012	0.011	0.008	0.003	0.004	0.008

Source: Author's calculations.

There was about a 19 per cent decline in poverty based on PHCI. Relative poverty incidence as measured by PHCI declined from nearly 39 per cent in 1994 to 38 per cent in1997 and reached 0.20 per cent in 2009 while the average PHCI for the panel period was 0.29 per cent. Besides, when it comes to the minimum amount of money relative to the poverty line required to bring all the poor to the level of the poverty line, the decline was even more evident using PGI and SPGI. According to these estimates, the depth of poverty PGI declined from nearly 5 per cent in 1994 to 2 per cent in 2009. This shows a reduction of 3 per cent over the panel period while the severity of poverty measured by SPGI declined from 1.2 per cent in 1994 to 0.4 per cent in 2009, which is a reduction of 8 per cent over the panel period. In general, the average for the three indices (PHCI, PGI and SPGI) for the whole panel period was 29.3, 3.6 and about 1 per cent respectively.

4.1.3. Analysis of Poverty using the Spells and Component Approaches

This section discusses the links between households' characteristics of poverty status from their inter-temporal poverty situation using the component and Spells measurements.

Poverty Decomposition: The Component Approach

Following the component approach a household was characterized as chronically poor when its time-mean consumption was below the poverty line and transiently poor if its time-mean consumption was above the poverty line but one of its consumption levels was below the poverty line. The decomposition shows that 20.2 per cent of the households were chronically poor while 43.3 per cent were transiently poor during the study period. Further, from same decomposition using index measures (from Equations 2 to 4 and given in Table 2.4), the chronic nature of poverty declined as the poverty index became more sensitive to the depth of poverty. This is reasonable because the more sensitive an index is to the depth of poverty, the more weight the transient component gives to a household that is poor in a year but not poor in the other year (relative to the chronic component which considers just the average income over a given period)(Gleww and Gibson, 2006).

Table 2.4 Poverty Decomposition (Component Approach) (NT = 2,630)

Poverty type	Headcount (P_0)	Poverty gap (P_1)	Squared poverty gap (P_2)
Transient poverty	0.144	0.014	0.002
Chronic poverty	0.249	0.022	0.005
Total poverty	0.293	0.036	0.008

Source: Author's calculations.

Poverty Decomposition: The Spells Approach

Tables 2.5 and 2.6 give figures of poverty decomposition using the Spells approach. This approach decomposes poverty by the number of times a household was poor. Table 2.5 shows that out of the poor households in the period 23.8, 19.8, 12.2, and 7.8 per cent became poor once, twice, three and four times respectively while only 0.9 per cent of the households were poor in all the panel years (or always poor). On the other hand, 35.5 per cent of the households were never poor throughout the period. Using the same approach and these poverty waves/categories we further aggregated the households into chronically poor (if the household was poor at least four times), transiently poor (if a household was poor one, two, three or four times) and never poor if a household was not poor for the entire panel period. This approach was used for identifying chronic and transient poverty. Accordingly, Table 2.5 presents the results following the Spells approach where we decomposed the households into chronic poor, transient poor and never poor categories. As Table 2.5 shows out of the 566 semi balanced panel consisting of 2,630 observations, 201 households (35.51 per cent) remained never poor, while 50 (8.83 per cent) households were chronically poor and the remaining 315 households (55.65 per cent) were transiently poor during the study period.

Table 2.5 Poverty Decomposition (Spells Approach) (NT = 2,630)

Poverty-Categories	Headcount		Percentage
	Overall	Between	
Transient-poor	1477	315	55.65
Chronic-poor	277	50	8.83
Never-poor	926	201	35.51
Total	2630	566	100.00

Source: Author's calculations.

According to the Spells approach, transient poverty accounted for more than 86 per cent of the total poor households. This reconfirms Kedir and McKay's (2005) findings that tackling urban poverty in Ethiopia requires a clear understanding of transient poverty. These figures also show that policies aimed at consumption smoothing for stemming inflows into transient poverty are important alongside those supporting the movement out of chronic poverty through sustained and short-term poverty alleviation strategies. In general, taking into account the limitations of the Spells approach we conclude that poverty was transitory in urban Ethiopia. This implies that poverty alleviation policies should focus on how to pull out the short-run poor from their poverty traps while giving due attention to long-run chronic poverty.

Table 2.6a and 2.6b give the results of decomposed poverty by the Spells approach in the number of times a household was poor by dividing it further into chronic poor, transient poor and never poor categories and mean values of major variables of households' characteristics and their evolution through poverty waves in urban Ethiopia during the study period. When it comes to the evolution of mean (percentage) values of major variables of households' characteristics through the poverty waves (Table 2.6a) the mean consumption expenditure declined with the number of times that a household was poor. As the number of times a household was poor increased, the percentage of head's employment, head's completion of secondary and tertiary schooling and households which received remittances declined. However, percentages of head's gender and completing primary schooling, household's family size and dependency ratio steadily increased with the number of times that a household was poor. The never poor households are often associated with smaller household size, less children and fewer dependent members than poor households. The heads of never poor households are also more likely to be younger, more educated and less females than poor households.

Table 2.6b gives details about the evolution of mean (percentage) values of major variables of households' characteristics in the chronic poor, transient poor and never poor poverty categories. The PCCE figures declined with the severity of poverty. Households in the never poor category had the highest mean PCCE of 5.35, the chronically poor category had the lowest level at 3.77 and the transient poor category was in the middle at 4.69. A greater proportion of poor households were female headed; they were only 40 per cent in the never poor and 48 per cent in the chronic poverty categories as compared to male headed households. There were not many variations in the transient poverty category. Forty-eight per cent female headed households in the chronic poverty category indicate their vulnerability to poverty. Chronic poverty is often strongly associated with households having a bigger family size and more children and consequently the highest dependency ratio compared to the other categories. The chronically poor households are often associated with a larger household size and more children and elders as compared to the never poor and transient poor households. The heads of always poor households are less likely to be younger, less educated and female as compared to the never poor and transient poor households.

The education variables show distinct differences between poverty categories. Only 15 per cent heads of households that were never poor were much less likely to have attained formal education as compared to the chronically poor of which 53 per cent were illiterate. This shows the strongest association between poverty categories and education characteristics. For instance, only 19 per cent of the heads in the transient poor category had completed secondary schooling, while about 30 per cent heads of households had completed secondary schooling in the never poor category.

Table 2.6a Mean (Percentage) Values of HH Characteristics by Poverty Wave (NT= 2,630)

Variables	Never poor	Poor once	Poor twice	Poor 3 times	Poor 4 times	Always poor
Ln PCCE	5.35	4.96	4.66	4.2	3.76	3.79
Head’s age	50.09	49.07	50.44	49.93	50.83	55.76
Head’s age-squared	26.97	26.12	27.41	27	27.23	32.79
Head’s gender (female)*	0.4	0.46	0.46	0.52	0.47	0.56
Family-size	4.99	5.25	5.57	5.4	6.09	6.32
Number of children	1.56	1.7	1.97	2.12	2.76	2.84
Number of elderly	0.3	0.28	0.3	0.2	0.08	0.16
Dependency-ratio	0.56	0.56	0.57	0.64	0.75	0.72
Head primary schooling-complete*	0.36	0.44	0.45	0.48	0.48	0.36
Head secondary schooling-complete*	0.3	0.21	0.2	0.12	0.13	0.12
Head tertiary schooling-complete*	0.11	0.07	0.02	0.01	0.01	0
Head’s employment*	0.52	0.5	0.43	0.45	0.42	0.44
Casual-worker-members #	0.08	0.15	0.14	0.25	0.28	0.24
Casual-worker member*	0.06	0.08	0.1	0.14	0.16	0.16
Received remittances*	0.17	0.18	0.13	0.07	0.04	0.08

Table 2.6b Mean (percentage) values of HH characteristics by poverty categories (NT=2,630)

Variable	Never poor	Transient poor	Chronic poor
Ln PCCE	5.35	4.69	3.77
Head’s age	50.09	49.74	51.37
Head’s age-squared	26.97	26.77	27.84
Head’s gender (female)*	0.40	0.47	0.48
Family-size	4.99	5.40	6.12
Number of children	1.56	1.89	2.77
Number of elderly	0.30	0.27	0.09
Dependency-ratio	0.56	0.58	0.75
Head primary schooling-complete*	0.36	0.45	0.47
Head secondary schooling-complete*	0.30	0.19	0.13
Head tertiary schooling-complete*	0.11	0.04	0.01
Head’s employment*	0.52	0.46	0.42
Casual-worker-members #	0.08	0.17	0.27
Casual-worker member*	0.06	0.10	0.16
Received remittance*	0.17	0.14	0.05

Source: Author’s calculations; Note: *: percentages.

Similarly, 11 per cent household heads in the never poor category had completed tertiary schooling, while this figure was 4 per cent for the transient poor and not more than 1 per cent for the chronically poor households. Low levels of education are clearly linked to chronic poverty as only 13 and 1 per cent of the chronically poor had completed secondary and tertiary schooling respectively. These figures provide some evidence on the strong negative relationship between education and poverty categories in general.

Poverty categories also varied with the value of remittances received by the households. On average 17 per cent of the never poor households received remittances, though the figure decreased consistently to 14 and 5 per cent for transient poor and chronically poor, respectively. Table 2.6b shows that there were significant numbers of unemployed heads in each poverty category, but the highest proportions were among the chronically poor as compared to the other groups as 52 per cent of the heads who had never been poor were employees, whereas for the chronically poor this figure was only 42 per cent and for transient poor it was 46 per cent. Among the chronically poor households, 16 per cent worked as casual workers compared to only6 per cent in the never poor and10 per cent in the transient poor categories. There was more casual worker members --27 per cent among the chronically poor and 8 per cent among the never poor categories.

4.2. Regression Results

This section presents the results of the complementary econometrics models to derive the exact change caused by the determinants. Multiple regressions –the standard robust FEM, bootstrapped REs Probit regression (estimated the marginal effects); bootstrapped QR; and the MNL model's regressions, independently on same explanatory variables were performed to achieve these results. The research used PCCE in logarithm term as the dependent variable for FEM and QR and binary choice (poor =1; 0 otherwise) for the RE Probit model. The dependent variable for the MNL model takes the value of zero, one and two for never poor, transiently poor and chronically poor as the categorical outcomes.

4.2.1. Results of the Consumption Model

This study used the robust (within) FEM and bootstrapped estimations in modeling welfare/PCCE in urban Ethiopia to diminish the heteroscedasticity problem. Besides, the data was also checked for its statistical diagnostic tests before conducting model estimations. It also used the variance inflation factor (VIF) to test the existence of multicollinearity in the hypothesized independent variables. The results show that there were no serious multicollinearity problems as VIF values were less than 10. The Breusch-Pagan LM test for random-effects revealed that there was no unobserved household heterogeneity as the p-value was greater than 0.05. Further, we performed the Hausman test for comparing the RE model with the FE model.

The results show that the fixed-effects estimation was more efficient than the random-effects model.

Table 2.7 gives the FE, Probit and QR estimates of the determinants of per capita consumption expenditure in urban Ethiopia. The first column gives the FEM results, the second shows the marginal effects of the Probit model and the remaining columns show bootstrapped QR estimates for the expenditure equation for different values of τ (at 10th, 25th, 50th, 75th and 90th quantiles respectively). The QR results reinforce the FE regression results. They share the same coefficient signs for most explanatory variables; they differ only by the magnitude of the coefficients. Hence, this offers an opportunity for a more complete view of the statistical landscape and the relationships among explanatory variables in different parts of the consumption expenditure distribution. Overall, the estimation results show that the model fits the data relatively well and most of the coefficients have expected signs and are statistically significant. Moreover, the use of robust standard errors and bootstrapped QR help diminish the heteroscedasticity problem. The results of the Probit regression are given for comparison purposes; this study analyzed results from the robust FEM and bootstrapped QR estimates.

Household Head Characteristics

The following results were obtained from FEM and QR. The estimated coefficients of the QR measure the impact of each covariate on the whole distribution and represent the percentage consumption changes for a household with median level of consumption expenditure. The regression results suggest that households' probability of being poor and the level of PCCE increased insignificantly throughout the expenditure quantile distribution with the age of the household head but was lower at very low and very high levels (as indicated by the negative coefficients of its square terms). PCCE fell in female headed household as they faced significantly lower probabilities of decreasing poverty and lower living standards as compared to male heads. This was evinced by the significant estimates of FEM and the bootstrapped marginal effects of random-effects (RE) Probit regression and QR estimates respectively. As for the corresponding parameters' estimates female household heads had 8.6 per cent lower consumption levels than male heads and about 3.9 per cent higher probability of being consumption poor ceteris paribus.

When it comes to the QR for the whole distribution, being headed by a female had a negative effect though the effect was statistically insignificant at the 10th and 25th quantiles. As for other quantiles, female household heads' disadvantages were robust significantly and the expenditure gap increased appreciably, which is consistent with distribution. The disadvantages faced by female household heads were higher at a higher expenditure distribution with higher magnitude of lowered living standards at the top of the expenditure distribution. Among those at the bottom of the significant distribution, the expenditure difference was around 14 per cent lower for female household heads than for male heads while at the top this difference increased and was lower by about 25 per cent for female household heads as compared to male heads. This is consistent with previous findings (for example, Jayamohan and Amenu, 2014) that female household heads in urban areas enjoyed lower aggregate consumption than their male counterparts.

Table 2.7 Modeling Welfare in Urban Ethiopia: Determinants of PCCE (NT = 2,630)

Explanatory variables	FEM	RE Probit	Bootstrapped Quantiles				
	Coef.	ME	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
	5.122***	-1.836***	3.703***	4.313***	5.285***	6.253***	6.563***
Constant	(0.294)	(0.533)	(0.335)	(0.265)	(0.204)	(0.243)	(0.405)
Household Head's Characteristics							
	0.003	0.003	0.013	0.009	0.005	-0.004	0.002
Age	(0.011)	(0.019)	(0.013)	(0.009)	(0.008)	(0.009)	(0.018)
	-0.006	-0.004	-0.011	-0.006	-0.004	0.001	-0.001
Age-squared	(0.010)	(0.018)	(0.013)	(0.008)	(0.008)	(0.008)	(0.018)
	-0.086**	0.039*	-0.045	-0.025	-0.140***	-0.237***	-0.204**
Gender (female)	(0.061)	(0.080)	(0.069)	(0.035)	(0.042)	(0.056)	(0.092)
Primary schooling-	0.129**	-0.086***	0.224***	0.217***	0.179***	0.158***	0.224**
complete	(0.051)	(0.095)	(0.052)	(0.039)	(0.038)	(0.050)	(0.088)
Secondary schooling-	0.282***	-0.18***	0.457***	0.478***	0.469***	0.427***	0.602***
complete	(0.063)	(0.129)	(0.063)	(0.059)	(0.066)	(0.066)	0.132)
Tertiary schooling-	0.348***	-0.403***	0.910***	0.837***	0.662***	0.697***	0.812***
complete	(0.094)	(0.240)	(0.093)	(0.066)	(0.076)	(0.140)	(0.110)
Household's Characteristics							
	-0.062***	0.075***	-0.143***	-0.127***	-0.106***	-0.090**	-0.087**
Family-size	(0.021)	0.044)	0.022)	(0.021)	(0.021)	(0.040)	0.044)
Family-size squared	0.468***	-0.408***	0.780***	0.733***	0.591***	0.572*	0.520*
	(0.126)	(0.343)	(0.104)	0.118)	0.138)	0.319)	0.314)
Dependency-ratio	-0.450***	0.187***	-0.512***	-0.520***	-0.601***	-0.742***	-0.548***
	(0.079)	(0.151)	(0.097)	(0.059)	(0.061)	(0.107)	(0.118)
	0.145**	-0.007*	0.094*	0.055	-0.038	-0.107*	-0.198**
Head's employment	(0.055)	(0.086)	(0.051)	(0.044)	(0.042)	(0.064)	(0.066)
	-0.064*	0.048*	-0.215**	-0.137	-0.159*	-0.290**	-0.329**
Casual-worker	(0.092)	(0.137)	(0.100)	(0.115)	(0.097)	(0.104)	(0.091)
Number of casual-	-0.157***	0.099***	-0.180***	-0.244***	-0.228***	-0.228***	-0.199**
workers member	(0.046)	(0.087)	(0.046)	(0.041)	(0.040)	(0.054)	(0.070)
	0.021***	-0.119***	0.192**	0.189***	0.169***	0.113	0.032
Received remittance	(0.056)	(0.117)	(0.080)	(0.062)	(0.055)	(0.092)	(0.075)
	0.286***	-0.137**	0.150**	0.278***	0.393***	0.480***	0.616**
Residence-Addis	(0.066)	(0.092)	(0.063)	(0.050)	(0.056)	(0.076)	(0.096)
Time = 1,…, 5; for yrs.	0.167***	-0.047***	0.138***	0.110***	0.111***	0.142***	0.143***
1994, 97, 2000, 04 &09	(0.015)	(0.027)	(0.023)	(0.011)	(0.012)	(0.021)	(0.028)
R^2/Pseudo R^2	0.447		0.124	0.136	0.146	0.187	0.221
Observations	566	566	2630	2630	2630	2630	2630
Log-likelihood		-1312.187					
F test or χ test	F(15,565)= 22.88***	Wald $\chi^2(15)$ = 279.81***					

Note: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$. The Probit estimates are marginal effects. The values in parentheses in the lower cells of the sub-table represent robust standard errors for FEM and bootstrapped standard errors both for the RE Probit and QR estimates for each explanatory variable.

Unlike the results for the gender of the household head, all educational characteristics of households specified in the models were associated with less adverse outcomes as consumption increased with schooling as a whole. The result suggests that an increase in educated household head had a positive effect on consumption expenditure which in turn implies its negative impact on the likelihood of being poor of the household. The marginal effects of the RE Probit regression, the estimated coefficients of FEM and expenditure distribution (QR) estimates show that the magnitude of the effects of education on a household's poverty and per capita expenditure increased as the educational levels increased. The coefficients of the FEM results show that one level more of the head's primary, secondary and tertiary schooling significantly improved upward mobility in consumption expenditure. The corresponding magnitudes show that the per capita consumption expenditure of urban households' increased by 13, 28 and 35 per cent for those households where the heads had completed primary, secondary and tertiary schooling respectively. The marginal effects of completing primary, secondary and tertiary schooling decreased the probability of being poor among urban households by around 8.6, 18 and more than 40 per cent respectively.

When it comes to the quantile distribution, the coefficients for education were positive and highly significant through the expenditure distribution. The returns decreased slightly as we move up from the bottom quantile to the highest one for primary, secondary and tertiary schooling till the 90 per cent expenditure distribution, at which it increased again. Hence, in the middle percentiles of conditional expenditure distribution, household head's education had a lower positive impact on living standards relative to the bottom and top percentiles. Moreover, there was a difference in the returns to the levels of education as more effect is seen as levels of schooling increased. For example, at 90 per cent expenditure distribution, the corresponding magnitudes show per capita consumption expenditure of the urban households' increasing by 22, 60 and 81 per cent for those households whose heads had completed primary, secondary and tertiary schooling respectively.

Household Characteristics

The regression results suggest that a change in a household's family size was significantly and negatively associated with consumption expenditure, its distribution and positively with the probability of the household being poor. Moreover, all regression results show that household size had a concave relation to consumption expenditure, its distribution and the probability of the household being poor which is exhibited by the signs of coefficients of household size and its squared terms. This shows that an increase in the size of a household was linked to a decrease in the household's per capita consumption level and hence increased the probability of the household being poor. The estimated parameter and the marginal effect suggest that an additional family member by one point led to around a 6.2 per cent reduction in the per capita consumption level and a 7.5 per cent increase in the probability of the household being poor respectively.

QR results suggest that an increase in household size was associated with a reduction in living standards (household's per capita consumption level) but at a decreasing rate as the percentage of the expenditure distribution increased. Hence, for urban households the higher the consumption levels of a household, the lower the household size effect. The bottom poorest 10 per cent households' real per capita expenditure decreased by around 14 per cent for any additional family member in a household while it decreased by around 8.7 per cent for the top richest 10 per cent households' real per capita expenditure. Moreover, the significance of the positive quadratic terms' estimate in FEM and QR suggests the existence of turning points after which an increase in household size resulted in an improvement in welfare.

As expected, the results show that the dependency ratio in a household was significantly negatively associated with consumption expenditure and its distribution and positively associated with the probability of the household being poor. This shows that an increase in the number of dependents in a given household reduced per capita expenditure levels hence increasing the probability of the household being poor. The corresponding estimates show that a household with more dependents had lower living standards and a higher probability of being poor by about 45 and 19 per cent respectively. When it comes to the magnitude of the coefficients' estimates as we go up to the higher quantiles the living standards fall monotonically for an increased dependency ratio. Consequently, the higher the consumption level of a household is, the larger the dependency ratio effect will be.

Regarding occupational characteristics, coefficients of the FEM on household heads with regular work or employed was positive, but was negative in the Probit model's estimates; both these were significantly so. The effect of the quantile model's distribution coefficients varied widely with mixed effects. It shows that a household head with regular work or who was employed influenced PCCE positively at lower quantiles but negatively influenced it at the higher quantiles. It is obvious that regular employment earners had a higher occupational return than other groups even though this advantage decreased as we move with the upper expenditure distribution. The estimated coefficient and marginal effect value shows that if the household head was a regular worker, the household will have higher per capita consumption expenditure and a lower probability of being poor by 15 and 0.7 per cent respectively. As for the magnitude of the QR, PCCE increased up to 12 per cent at the 10^{th} quantile and lowered to 20 per cent at the 90^{th} quantile. Contrarily the coefficients of household members being casual workers were negative in all the models. The effect was strong and significant at the 1 per cent level for households with large numbers of casual-worker members implying that additional members as casual-worker members decreased PCCE by 16 per cent, hence aggravating the probability of the household being poor by 4.6 per cent. The effects of the quantile model's distribution coefficients, varied widely; as we move up the conditional expenditure distribution, the per capita expenditure of the casual employed worker fell rapidly with consistent lowest returns. The same was also true for households with large numbers of casual-worker members with a magnitude as low as 18 per cent at the 10^{th} quantile and as high as 22 per cent at the highest quantile.

Another important variable that affected consumption expenditure positively and significantly and was hence opposite of the households' poverty was the remittances that the households received over time. It shows that the inflow of remittances to a household increased its consumption level by 2.1 per cent and reduced the likelihood of the household's poverty by 11.9 per cent ceteris paribus. The QR results show that an increase in remittances increased the per capita expenditure but decreasingly as the consumption expenditure distribution increased. However, the results are significant only for the bottom and middle parts (10^{th}, 25^{th} and 50^{th}) of the QR. Location of residence also had a strong association with household PCCE and poverty. Residing in capital Addis Ababa had higher PCCE by 29 per cent and the likelihood of a household falling in poverty by 14 per cent as compared to households residing in other cities ceteris paribus. Moreover, as for the quantile model's distribution, the magnitude of the coefficients' estimate shows that living standards improved as expenditure distribution increased. This may be due to the relatively more job opportunities in the capital mainly due to the growing informal sector. As a result, this contributed to a lower probability of a household falling into poverty. Lastly, the regression results show that consumption expenditure increased significantly through the panel period though the increasing percentage levels varied as the consumption expenditure distribution increased.

4.2.2. Results of the MNL Model

Exploiting advantages of the multinomial logistic model that permits an analysis of decisions across more than two categories (Wooldridge, 2002) we did the MNL regression taking the values of zero, one and two for never poor, transiently poor and chronically poor respectively as the dependent variable. The never poor group was set as the reference group and so it estimates a model for chronic poor relative to non-poor and for transient poor relative to non-poor. Accordingly, we obtained robust estimates for the three categories relative to the first group (the never poor). However, as the coefficients of the MNL model cannot be interpreted directly but in terms of their marginal effects (Greene, 2007) Table 2.8 presents marginal effects, their statistical significance and robust standard errors from the MNL regression results corresponding to Equations 10-13. As Table 2.8 shows most of the parameter estimates from the model are of expected signs and different from zero at the 5 per cent or lower significance levels. The overall model is significant at the 1 per cent level and the pseudo R^2-indicates that the model shows that most of the explanatory variables significantly influenced both the nature of the poverty categories and the never poor group.

Our empirical findings (Table 2.8) confirm that the gender (female) and age of the household head; family size and dependency ratio; casual-worker members; and the number of casual-workers are positively and significantly related to the likelihood of a household being chronically poor. On the other hand, all educational levels, household head's employment, remittances and location of residence are associated negatively and significantly with a household being chronically poor. Family-size, casual-worker members and number of casual-workers in a household are positively and significantly related to the household's transient poverty, while head's age, all educational levels, dependency-ratio, remittances and location of residence are significantly and negatively related to a household's transient poverty. This shows that these variables had a significant effect on the level of both poverty categories, which means that a one unit increase in the respective variables could increase or reduce poverty levels by the same unit according to the sign of the corresponding marginal effects ceteris paribus.

Table 2.8 MNL Model Result: Determinants of Chronic and Transient Poverty (N = 2,630)

	Transient poor			Chronic poor		
Explanatory variables	Coef.	SE(Robust)	Marginal Effects	Coef.	SE(Robust)	Marginal Effects
Households head's characteristics						
Head's age	-0.061^{***}	0.019	-0.016	0.049^{*}	0.042	0.004
Head's age-squared	0.047^{**}	0.018	0.012	-0.05^{**}	0.039	-0.003
Head's gender (female)	0.138^{**}	0.101	0.021	0.419^{**}	0.176	0.014
Head 1^{ry}-schooling-completed	-0.193^{*}	0.115	-0.031	-0.571^{**}	0.2	-0.019
Head 2^{dry}-schooling-completed	-0.908^{***}	0.136	-0.195	-1.300^{***}	0.264	-0.027
Head 3^{ry}-schooling-completed	-1.448^{***}	0.204	-0.316	-2.655^{***}	0.636	-0.042
Household's characteristics						
Family-size	0.144^{***}	0.043	0.012	0.902^{***}	0.134	0.035
Family-size squared	-0.441^{*}	0.297	-0.029	-4.987^{***}	1.023	-0.201
Dependency-ratio	-0.049	0.151	-0.065	1.990^{***}	0.344	0.086
Head's employment	-0.122	0.104	-0.018	-0.426^{**}	0.2	-0.015
Number of casual-workers	0.526^{***}	0.13	0.105	0.769^{***}	0.168	0.019
Casual-worker member	0.437^{**}	0.189	0.086	0.679^{**}	0.285	0.017
Received remittance	-0.273^{**}	0.125	-0.043	-1.230^{***}	0.326	-0.033
Residence Addis	-0.157	0.093	-0.021	-1.374^{***}	0.212	-0.054
Time trend	-0.053	0.034	-0.011	-0.076	0.063	-0.002
Constant	1.797^{***}	0.512		-7.622^{***}	1.286	
Log-pseudo likelihood = -2150.001						Wald $\chi^2(30)$ = 347.38
Pseudo R^2 =0.095						Prob>χ^2 =0.0000

Note: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Household Head's Characteristics

The effect of age of household head on poverty categories shows that the older a poor household head the less likely it is that the household's poverty was transient and more likely that it was significantly chronic. These may be due to being continuously poor without a single chance of out of poverty for a long period at old age, gaining a more number of life ages aggravate the probability of being chronically poor. The converse is true for the transient poverty. Ceteris paribus, the corresponding marginal effect value suggests that an increased age of the head decreased transient poverty by 2 per cent and that an increased age of the head increased the likelihood that s/he was chronically poor by 0.4 per cent. In contrast, while positively affecting the transient poor; age-squared had a negative impact on the chronic poor significantly in both cases. The results also show that an increase in the age of the household head increased the probability of the household never being poor. Moreover, the significance of the quadratic term in the regression suggests the existence of turning points after which an increase in age of the head results in a counter effect on the poverty status of the household. The marginal effect value of the household's age-squared shows that increases in experience increased the probability of the household being transient poor significantly while it reduced its probability of being never poor and chronically poor significantly.

The regression results suggest that a household being female headed was positively associated with the likelihood of its being chronically poor and transient poor significantly. Hence, it was associated negatively to the probability of never being poor, suggesting that an increased number of female heads increased the likelihood that the households were poor with more severity in being transitory poor. Ceteris paribus, a 1 per cent increase in being a female headed household increased the likelihood that the household would be poor by 2.1 per cent and chronically poor by 1.4 per cent. MNL results show that all levels of education variables categorized in this study significantly and negatively impacted both poverty categories. Hence, an increase in these factors reduced the poverty categories ceteris paribus. This also shows that a household head's educational levels or an increase in each level increased the probability of the household being never poor, with more returns as schooling levels increased. Moreover, the results confirm that the influence of education was in accordance with the descriptive analysis that a higher level of the head's education mattered more in reducing the household's chances of being transient poor as it had the largest marginal effect values. The corresponding marginal effect suggests that one additional level of primary schooling reduced transient poverty by 3.1 per cent and reduced chronic poverty by only 1.9 per cent. Similarly, an additional level of secondary schooling reduced transient poverty by 19.5per cent and reduced chronic poverty by 2.7 per cent and a one additional level of tertiary schooling reduced transient poverty and chronic poverty by 31.6 and 4.2 per cent respectively.

Household Characteristics

Family size was positively associated with the chronic and transient poverty categories significantly. The positive association of family size with poverty categories of urban households suggests that an increase in the household size meant that the household was more likely to fall into poverty, that is, it was less likely to fall in the never being poor group. Further, the opposite sign in the estimate of the quadratic terms in both cases suggests the existence of turning points after which an increase in household size resulted in counter effects on the probability of a household being never poor and poverty categories of the household. Their marginal effect suggests that an increase in the number of household members by one member increased the probability of the household being transitory poor by 1.2 per cent and the probability of its being chronically poor by 3.5 per cent ceteris paribus. The dependency ratio to poverty categories shows that the more possibility of an increase in the number of dependent members in a household, the less likely that the household's poverty was transient and more likely that it was chronic. The effect was significantly stronger on the probability of the household falling into the chronic poor category. Ceteris paribus, the marginal effect value suggests that an increase in the dependency ratio of the household increased the likelihood of its being chronically poor by 8.6 per cent.

Regarding socioeconomic characteristics, employment activities were important determinants of all poverty categories. Head's employment significantly impacted the likelihood of the household being in chronic poverty negatively. Hence, households headed by employed heads had a 1.5 per cent less probability of being in chronic poverty. The head being a casual worker impacted the likelihood of the household being in either of the poverty categories significantly and positively. The marginal effect value suggests that households headed by a casual worker had 10.5 per cent higher probability of being in transient poverty and a 2 per cent less probability of being chronic poor ceteris paribus. Similarly, households having more casual-worker members were significantly and positively associated with being in either of the poverty categories. Households with an additional number of casual-worker members had a 8.6 per cent higher probability of being in transient poverty and a 1.7 per cent higher probability of being in chronic poverty.

The regression results show that the inflow of remittances to a household was significantly and negatively associated with the likelihood that it was chronic and transient poor. It shows that the inflow of remittances to the household decreased the probability of its being transient poor and chronic poor and hence increased the probability of its being never poor. Ceteris paribus a 1 per cent increase in remittance flows decreased the likelihood of the household being transient poor by 4.3 per cent and reduced the likelihood of chronic poverty by 3.3 per cent. Location of residence also had a strong association with household poverty as residential differences considerably affected the livelihoods of the urban poor negatively. It appears that residing in Addis Ababa contributed to decreasing a household's probability of being chronic poor significantly (5.4 per cent). This may be due to the relatively more job opportunities in the capital mainly due to the growing informal sector. As a result, this contributed to increasing a household's probability of improving its poverty situation. Lastly the empirical findings suggest a declining trend in overall poverty situations ceteris paribus. The probability of being transient poor and chronic poor has decreased which increases the probability of households never being poor over time even though the magnitude of the marginal effects is low.

5. Conclusions and Policy Implications

This essay provided a descriptive and econometric analysis of the determinants of per capita consumption expenditure (PCCE) and poverty dynamics in urban Ethiopia using EUHS's five round panel data covering the period 1994 to 2009. The study used consumption expenditure to measure the poverty levels and analyzed the determinants of expenditure and poverty status in urban Ethiopia. The study used the FGT indices to measure poverty and both component and Spells approaches for decomposing poverty into chronic and transient poverty. The study also used two groups of econometric analyses in two parts: first, it looked at the determinants of PCCE through fixed-effects and conditional QR models at mean and different quartiles and second, it explored the determinants of chronic and transient poverty using a categorical multinomial logistic regression (MNL) model. The two methods/parts are distinct but complementary in an analysis of expenditure and poverty and its dynamics. The first part (the consumption models) shed light on the key determinants of consumption poverty, while the second model (the MNL model) provides a picture of poverty which helps identify target groups to which the government can direct its poverty alleviation strategies.

Consistent with previous findings of poverty studies in sub-Saharan Africa, the results of all the models used in this essay confirmed the importance and statistically strong dependence of most of the household heads' characteristics and households' characteristics and PCCE and also poverty categories. The findings show that while a large number of households frequently moved in and out of poverty between the panel periods, many did not move far above the poverty line and remained vulnerable to falling back into poverty. The FGT measures show that poverty incidence, depth and severity consistently declined over time. The Spells approach poverty measurement indicates that more than 8 per cent of the households were trapped in chronic poverty while 56 per cent were affected by transient poverty. From this one can conclude that poverty as measured by household consumption expenditure declined over the study period. The study highlights that transient poverty remained high compared to chronic poverty with approximately 84 percent of the poor households being transiently poor.

The regression results suggest that household head's characteristics and household's characteristics mattered for a household's welfare and poverty categories. The results of FEM and QR show that household head's age and family size had an inverse U-shape influence on consumption expenditure and that PCCE fell with family size but at a decreasing rate as we moved up to the right side of the whole distribution significantly. The results from the same regressions also confirm that gender (female), age, primary, secondary and tertiary education, employment of the household head, remittances and location of the residence were significantly important determinants of a household's consumption expenditure. The findings show that female headed households had a lower expenditure level than male headed households. Most educational characteristics of heads of households were associated with less adverse outcomes as PCCE increased with additional levels of education. For QR we found that although returns to schooling were positive in all the quantiles, education was relatively more valued by households with higher levels of consumption. An increase in the size of a household was linked to a decrease in its per capita consumption level but at a decreasing rate as the percentile of the expenditure distribution increased. In contrast, dependency ratio had a negative impact on PCCE level, suggesting a lower PCCE for urban poor as compared to households with a large share of dependents.

Regarding occupational characteristics, coefficients from the FE model on household head with regular work were positive while the effects varied with mixed signs as per the quantiles models. This shows that PCCE was influenced positively for employed heads at lower quantiles but negatively for higher quantiles. Contrarily, the coefficients of household members being casual workers were related negatively to PCCE in all models indicating a negative effect of household work composition on PCCE. The effect was significantly strong for households with a large number of casual-worker members implying that additional members as casual workers decreased PCCE, hence aggravating the probability of the household being poor. The results also show that the value of remittances that the households received over time affected PCCE positively. QR results show that an increase in the inflow of remittances increased the per capita expenditure of households but decreasingly as the distribution increased. Location of residence also had a strong association with household PCCE and poverty; residing in capital Addis Ababa had higher PCCE. Lastly, the regression results show that consumption expenditure increased significantly over the panel period.

MNL's results show that a household being headed by a female was significantly and positively associated with the likelihood that the household was chronic poor and transient poor. Moreover, MNL's regression results suggest that household head's characteristics such as completion of primary, secondary and tertiary schooling, employment, remittances and location of residence significantly reduced both chronic and transient poverty of the household. On the other hand, the results also show that a household's family size and dependency-ratio; casual-worker members and number of casual-worker members significantly aggravated both poverty categories. The empirical findings show that the age of the household head impacted the poverty categories oppositely. The results show that the older the head of a poor household, the less likely it is that the household's poverty was transient and more likely that the household's poverty was chronic. This shows that these variables had a significant effect on both the poverty categories. This means that a one unit increase in the respective variables could increase or reduce poverty levels by the same unit according to the sign of the corresponding marginal effects ceteris paribus. In general, the findings suggest that age; educational level and employment status of the household head, remittances and the location of residence played a critical role in increasing the likelihood of a household being never poor, while the head's gender and household size aggravated the likelihood of the household falling into poverty.

These findings are important and can be used to initiate policy options for reducing poverty based on the assumption that any policy which is good for welfare improvement will also be good for poverty reduction provided the fact that many of non-poor households are above the poverty line and very sensitive to changes and can fall back into poverty. Policies that aim at reducing family size, dependency ratio, encouraging remittances and improving access to education and employment activities will exert a positive effect on PCCE and help in reducing urban poverty. Household heads' characteristics and households' characteristics are important determinants of either of the poverty categories and are important poverty reduction strategies. Targeting of policies will be more effective if they take these characteristics into consideration while tackling poverty.

REFERENCES

Alem, Y. (2014). Poverty Persistence and intra-household heterogeneity in occupations: Evidence from urban Ethiopia. *Oxford Development Studies*, 43(1): 20-24.

Alem, Y. and M. Soderblom (2012). Household level consumption in Urban Ethiopia: The effects of a large food price shock. *World Development*, 40(1): 146-62

Alem, Y., G. Kohlin, and J. Stage (2014). The Persistence of Subjective Poverty in Urban Ethiopia. *World Development* 56: 51-61

Baulch, B. and N. McCulloch (2003). Being poor and becoming poor: poverty status and poverty transitions in rural Pakistan. *Journal of African and Asian Studies*, 37(2): 168-85

Becketti, S., W. Gould, L. Lillard,and F. Welch (1988).The panel study of income dynamics after fourteen years: An Evaluation. *Journal of Labor Economics*, 6 (4): 472-92.

Bigsten, A. and A. Shimeles (2008). Poverty transition and persistence in Ethiopia. *World Development*, 36(9): 1559-84.

Central Statistical Agency (CSA) (2007). *Country Population and Housing Census Report-2007*. Addis Ababa: The Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development (MoFED).

Dercon, S. (2004). Growth and shocks; Evidence from rural Ethiopia. *Journal of Development Economics*, 74(2): 306-29.

Dercon, S. and P. Krishnan (1998). Changes in poverty in rural Ethiopia 1989-1995: Measurement, robustness tests and decomposition. CSAE working paper series, 1998-7.

Dercon, S. and Tadesse, M. (1999). A comparison of poverty in rural and urban Ethiopia. *Ethiopian Journal of Economics*, (8): 83-98.

Dercon, S., J. Hoddinott, and T. Woldehanna (2005). Shocks and consumption in15 Ethiopian villages: 1999-2004. *Journal of African Economies*, 14(4): 559-85

Efron B. and R. J. Tibshirani(1994). *An Introduction to the Bootstrap*. New York: Chapman and Hall.

Engvall, A. and A. Kokko(2007). *Land and Human Development in Cambodia*. Phnom Penh: UNDP.

Fitzgerald, J., P. Gottschalk, and R. Moffit (1998). An Analysis of Sample Attrition in Panel Data. *Journal of Human Resources:* 33(2): 251–99.

Foster, J., J.Greer, and E. Thorbecke (1984). A class of decomposable poverty measures. *Econometrica*, 52(3):761–66.

Glewwe, P. and J. Gibson (2006).'Analysis of Poverty Dynamics', in *Handbook of Poverty Statistics.* New York: United Nations Statistical Division, pp. 324–69.

Greene, W. H. (2007). *Econometric analysis*, 4th ed. New Jersey: Prentice-Hall.

Greer, J. and E. Thorbecke (1986). A Methodology for Measuring Food Poverty Applied to Kenya. *Journal of Development Economics,*24 (1): 59-74.

Haddad, L. and A. Ahmed (2003). Chronic and Transitory Poverty: Evidence from Egypt 1997–1999. *World Development*, 31(1), 71–85.

Haughton, J. and S. Khandker (2009). *World Bank Handbook of Poverty Analysis.* Washington, DC: The World Bank.

Jalan, J. and M. Ravallion (1998). Determinants of Transient and Chronic Poverty: Evidence from Rural China. The World Bank Policy Research Working Paper No. 1936

Jalan, J. and M. Ravallion (2000). Is Transient Poverty Different? Evidence from Rural China. *Journal of Development Studies*, 36(6): 82-100.

Jayamohan, M.K. and T. K. Amenu (2014). Gender and poverty – an analysis of urban poverty in Ethiopia. *Development Studies Research,* Routledge 1:1, 233-243

Kakwani, N. and J. Silber (eds), (2008). *Quantitative Approaches to Multidimensional Poverty Measurement*. UK: Palgrave-Macmillan.

Kedir, A. and R. Disney(2004). 'Prices in the measurement of food poverty in urban Ethiopia, EEA', Proceeding of the first international conference on Ethiopian Economy, 3.

Kedir, M. and A. McKay (2005). Chronic poverty in urban Ethiopia: Panel data evidence. *International Planning Studies*, 10(1): 49-67.

Koenker. R. (2005).*Quantile Regression.*UK: Cambridge University Press.

Koenker, R. and G. Basset(1978). Regression quantiles. *Econometrica,* 46(1): 1-26.

Lipton, M. and M. Ravallion (1994). 'Poverty and Policy', in *Handbook of Development Economics 3*. Amsterdam: North-Holland.

McCulloch, N. and N. Baulch(2000). Simulating the impact of policy upon chronic & transitory poverty in rural Pakistan. *Journal of Development Studies,* 36(6): 100-30.

Meenakshi, J.V. and R. Ray (2002). Impact of Household Size and Family Composition on Poverty in Rural India. *Journal of Policy Modeling*, 24: 539-59.

Mincer, J. (1994). *Schooling, Experience, and Earnings. Human Behavior and Social Institutions No. 2.*New York: National Bureau of Economic Research.

Ministry of Finance and Economic Development (MoFED) (2010). *Growth and Transformation Plan I,* volume 1.Addis Ababa: The Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development.

Mok, T. Y., C. Gan, and A. Sanyal (2007). The determinants of urban household poverty in Malaysia. *Journal of Social Sciences*, 3 (4): 190-96.

Nathan F. O., J.A.O.Jonathan, and A. Asafa (2002). Determinants of Regional Poverty in Uganda. AERC working Paper122, Nairobi.

Olaniyan, O. (2000). *The Role of Household Endowment in Determining Poverty in Nigeria*. Ibadan, Nigeria: University of Ibadan, Department of Economics.

Ravallion, M. and B. Bidani (1994). How Robust Is a Poverty Profile? *The World Bank Economic Review*, 8(1): 75-102.

Sen, A. (1976). Poverty and Ordinal Approach to Measurement. *Econometrica*, 44(2): 219-31.

Sengupta, J. (2007). *A Nation in Transition: Understanding the Indian Economy*. New Delhi: Academic Foundation.

Shinkai, N. (2006). *Infrastructure Development and Poverty Reduction: The Case of Vietnam*. Forum of International Development Studies, 32. Nagoya: GSID

Tesfaye, A. (2006). *The analysis of Urban Poverty in Ethiopia.* Australia: University of Sydney, NSW.

The World Bank (1996). *Taking Action for Poverty Alleviation in Sub-Saharan Africa*: A Report of an African Taskforce. Washington, DC: The World Bank.

The World Bank (2013). *East Asia Economic Update, Emerging Stronger from the Crisis*. Washington, DC: The World Bank.

Tong, K. (2011). Transient and Chronic Poverty in Nine Villages of Cambodia: Panel Data Evidence—Asset Approach. *Annual Development Review:*127–40.

United Nations Development Program(2000). *Human Development Report 2000*. New York: UNDP.

United Nations Development Program (2014) *Human Development Report 2014*. New York: UNDP.

Wooldridge, J.M. (2002). *Econometric analysis of cross-section and panel data*. Cambridge, Massachusetts: The MIT Press.

CHAPTER THREE

Impact of Weather Variations on Cereal Productivity and the Influence of Agro-Ecological Differences on Ethiopian Cereal Production[2]

Abstract

This essay investigates the impact of weather variations on cereal productivity in Ethiopia over a period of 15 years. The analysis is based on a panel sample of smallholder farm households across eight farmers' associations (FAs) in rural Ethiopia. The descriptive results show that cereal production and productivity increased over the period in the study area and in each agro-ecological zone (AEZ). The average annual rainfall distribution/trend declined, while annual temperatures increased through the study period. The econometrics results indicate that agro-chemicals, livestock, number of plots, education and agricultural extension services significantly enhanced cereal productivity while land quality and household head's age significantly influenced cereal productivity negatively. The regression results show that annual and seasonal weather variations, both in their linear and quadratic terms, significantly influenced cereal productivity. Moreover, the results provide evidence of agro-ecological differences and cereal productivity progress over time. These findings are important as they can be used for initiating government policy options when planning climate change adaptation strategies and agricultural policies tailored to support various AEZs across the country. Having poverty and food security implications, the essay recommends having public policies that are geared at improving agricultural extension services, farmers' education, supply of agricultural inputs and climate change adaptation strategies and policies that could meet farmers' needs; they also need to be suitable for the AEZs.

Keywords: Weather variations, cereal productivity, agro-ecological zones, panel data, Ethiopia.

JEL Classification Codes: C23, D13, D23, D24, E23, O13, Q54, Q56.

---

[2]An earlier version of this study is published in A. Heshmati (ed.) (2017). *Economic Transformation for Poverty Reduction in Africa: A Multidimensional Approach*. London: Routledge. Comments and suggestions on an earlier version of this paper by Giannis Karagiannis are gratefully acknowledged.

1. Introduction

While climate change is a global phenomenon, its potential effects are not uniform; instead they are unevenly distributed both between and within countries (O'Brien and Leichenko, 2008). To a large degree the extent of these impacts will depend on agro-climatic/ecological characteristics and the extent of local and national adaptation and adaptive capacities. There is consensus that over the coming decades, anthropogenic climate changes will cause dramatic transformations in the biophysical system that will affect human settlements, the ecosystem, water resources and food production, all of which are closely linked to human livelihood (IPCC, 2012). These transformations are likely to have widespread implications for individuals, communities, regions and nations. In particular, poor natural resource-dependent rural households will bear a disproportionate burden of the adverse impacts. Research findings reveal that weather variability due to climate change has a significant impact on global and regional food production systems, which in turn increases uncertainty about future incomes. This will have a serious impact on agriculture and poverty in developing countries particularly in SSA (UN-OHRLLS, 2009). Climate change effects poverty and food insecurity and fuels rising prices for staple grains that may result in a substantial reduction in real incomes and thus an increase in poverty especially for households spending large shares of their incomes on staple grains. The poverty effect of climate change is enormous in SSA where the yield impact of climate change is severe (characterized by low productivity) with no stratum experiencing significant poverty reductions.

Ethiopia's agricultural production is dominated by subsistence farmers making the country one of the most vulnerable to weather variabilities and climate change on the continent. The sector, contributing the largest share to the national GDP, provides employment and livelihoods to more than 80 per cent of the country's population. It contributes 81 per cent to the country's total export earnings and as the primary source of food provides up to 85 per cent of the country's food supplies (AfDB, 2016). According to NPC, on average, in 2016 agriculture grew by 6.6 per cent during the country's first Growth and Transformation Plan (GTP I) while its share in GDP averaged 41.5 percent in 2010. This declined consistently and finally reached 38.5 per cent by 2015 (NPC, 2016). However, the country's agricultural production is characterized by high dependency on rainfall, traditional technologies, high population pressure and severe land degradation. All this is compounded by one of the lowest productivity levels in the world. The sector is largely dominated by subsistence and smallholders who have less capacity to adapt to climate change and who on average cultivate areas less than 1.5 hectares (FAO, 2009). Ethiopia's ecological system is fragile and vulnerable to climate change; it is also characterized by diverse topographic features that have led to the existence of a range of agro-ecological zones each with distinctly varied climatic conditions.

Cereals are the major food crop of the country which are especially vulnerable to the adversities of weather variability and climate change and are characterized by poor productivity. Cereals are particularly important for the country's food security; are a principal dietary staple for most of the population; they also comprise about two-third of the agricultural GDP and one-third of the national GDP and are a source of income for a majority of Ethiopia's population. Cereals are vital to the country's crop production in terms of production volume, planted area and farm-households. According to CSA (2014) cereals had a share of more than 79 per cent of the total crop area and 85 per cent of grain crop production for the Meher season in the 2014 production year. Moreover, 81 per cent of the farmers – particularly those concentrated in central Ethiopia --- practice mixed farming and are primarily cereal producers.

Cereal production was marked by remarkable growth in Ethiopian crop production during the last decade. Several CSA publications (Table 3.1) show that total cereal production grew consistently from 2004 to 2014, from an average of 16 million metric tons in 2004-08 to 21.6million metric tons in 2009-14, averaging 18.8 million metric tons during the last decade. This means that cereal crop production had 27.4 per cent growth from 2004 to 2014 at a rate of 2.74 per cent per annum.

Table 3.1 Cereal production, planted area and yield trends for Meher season (2004–14)

Years	2004–08	2009	2010	2011	2012	2013	2014
Output (million Qt.)	16.0	155.3	177.6	188.1	196.5	215.8	360.1
Hectare (million Hec.)	9.3	9.2	9.7	9.6	9.6	9.8	10.1
Yield (Qt. /Hec.)	1.72	16.9	18.3	19.6	20.5	22.0	35.65

Source: CSA publications.

The productivity of the sector has shown steady growth in the last two decades (Kassahun, 2011). However, as per MoFED (2010), Ethiopia annually loses 2 to 6 per cent of its total production due to the effect of climate change. In sum, because of significant dependence on the agricultural sector for production, employment and farm household revenues, Ethiopia is seriously threatened by climate change, which leads to weather variations and frequent (sometimes prolonged) droughts and flooding all of which have impact the production of food crops, poverty and food insecurity.

In a conventional rain-fed farming system like Ethiopia, farmers use direct factors of production to produce several outputs. However, farmers' abilities to operate efficiently often depend on production risks like weather factors, agro-ecological characteristics, operational conditions and practices (like the production environment) and farm-specific characteristics (like technology selection or/and managerial practices). Hence, production is influenced by weather, agro-ecological and farm-household characteristics which by extension affect farmers' efficiency and productivity. Several empirical studies investigate the impact of climate change on Ethiopian agriculture using different methodologies (see Bamlaku et al., 2009; Bezabih et al., 2014; Kassahun 2011). However, several of these studies assess long-term climate change patterns rather than weather variability that captures short term patterns; some base their investigations on a single crop while others look at the national level.

Climate change may have short term effects due to weather variations or/and area-specific effects for which agro-ecology based analyses, for example, may provide better insights.

Consequently, there is dearth of literature that links short term weather effects and the influence of agro-ecological factors on farm-level cereal productivity; as a result, these links have not been fully understood. My research is designed to bridge this gap by providing an analysis of the impact of weather variation son cereal productivity and the influence of agro-ecological differences on cereal producers. It aims to answer the question: how do production risks --- weather factors, agro-ecological and farm-households' demographic and socioeconomic characteristics-- influence cereal production and productivity in main cereal crop producing regions in Ethiopia?

This study makes significant contributions to existing literature on the impact of climate change on crop productivity. First, while the effects of annual and seasonal weather variations capturing short term patterns are likely to differ from the long-term patterns of climate change, these possible differentials have not been thoroughly assessed in previous related studies in Ethiopia. To the extent that the patterns of climate change mimic weather uncertainty, policy measures aimed at mitigating the impacts of climate change could also serve the same purpose as those for weather uncertainty. This distinction is highly relevant in a setting like Ethiopia where both seasonal and yearly variations in rainfall are huge and rainfall is also hugely erratic. Second, the study makes an important methodological contribution to existing methodologies in its approach as it introduces a methodological innovation in literature on the impact of climate change by employing a combination of a standard production function, production risk and damage control framework approach as a model. It analyzes unbalanced panel data typically applying a fixed-effects model that enables keeping the time-variant effects of annual and seasonal weather and at the same time controlling for unobserved time-invariant effects at a farm-household level that potentially lead to omitted variable bias in cross-sectional Ricardian studies. Finally, the study incorporates agro-ecological factors, other exogenous factors and weather factors over a shorter period of time as opposed to long-term average climate variables normally used in a Ricardian analysis. Its AEZ analysis considers cereal cropping activities on a farm and is therefore replicable elsewhere in the country, between regions and within AEZs. The study provides valuable information which is needed for developing agro-ecologically adaptive strategies in response to the impact of climate change on crop production with growth, poverty and food security implications.

The rest of the essay is organized as follows. Section 2 presents a review of empirical literature and an overview of climatic conditions in Ethiopia. Section 3 discusses the method and the data for the study. Section 4 presents and discusses empirical findings and Section 5 gives a conclusion and recommendations.

2. Review of Empirical Literature

2.1 Impact of Climate/Weather Variations on Crop Productivity

Studies on the impact of climate change on crop productivity have increased over the decades with a more recent focus on developing countries in general, and a specific focus on Africa. Most of these studies assess and show significant negative effects of climate change particularly for farmers in developing countries suggesting the extent to which adequate mitigation measures and adaptation options can lessen the expected climate impact (Yohannes, 2016). In what follows, this essay reviews the studies that focus on the impact of climate change on crop productivity in developing countries in general; this is followed by a review of studies on Ethiopia.

Liangzhi et al., (2005) investigated climate impact on Chinese wheat yields using time series and cross-section data for 1979-2000 for major wheat producing provinces and corresponding climate data like temperature, rainfall and solar radiation. They found that a 1 per cent increase in the temperature in the wheat growing season reduced wheat yields. They also report that rising temperatures over the two decades prior to their study accounted for a 2.4 per cent decline in wheat yields, while a major growth in wheat yields came from increased use of physical inputs. Guiteras (2009) estimated the impact of climate change on Indian agriculture using the FGLS estimation method. His results suggest that climate change is likely to impose significant costs on the economy unless farmers can quickly recognize and adapt to increasing temperatures. The study further reported that such rapid adaptation may be less plausible in a developing country where access to information and capital for adjustment is limited. Lee et al., (2012) analyzed the impact of climate change on agricultural production in 13 Asian countries. Their study used the agricultural production model and estimated the fixed effects panel model for agricultural production using seasonal climate variables and other input variables. Their results show that higher temperatures and more precipitation in summer increased agricultural production while higher fall in temperatures was harmful in South and Southeast Asia. They report that an overall increase in annual temperature decreased agricultural production. Addai and Owusu (2014) analyzed the sources of technical efficiency of maize farmers across AEZs in Ghana using a stochastic production frontier panel data model. They report that extension, mono-cropping, land ownership and access to credit positively influenced technical efficiency. High input prices, inadequate capital and irregularity of rainfall were the most pressing problems facing maize producers in the forest, transitional and savannah zones respectively.

Several empirical works investigated the impact of climate variations on agriculture at different levels using different methodologies in the Ethiopian context. Bamlaku et al., (2009) investigated efficiency variations and factors causing inefficiencies across AEZs in Ethiopia using a stochastic frontier analysis. They show that seasonal climate conditions and agro-ecological settings had a significant impact on technical efficiency. Their study also observes that education, proximity to markets and access to credit contributed to a significant reduction in farm inefficiencies.

In his analysis of climate variability and its economic impact on agricultural crops, Kassahun (2011) analyzed the marginal effects of temperature and rainfall on crop productivity using the Ricardian approach based on farm data generated from 174 farmers. He found that climate, socioeconomic and soil variables had a significant impact on farmers' net revenue per hectare. His results from a marginal analysis show that a 1°C increase in temperature during the main rainy and dry seasons reduced net revenues. He also reports that a 1°C increase in temperature during the short rainy and autumn seasons marginally increased net revenue per hectare. Further, this study also reported that an increase in precipitation by 1mm during the main rainy and dry seasons reduced net revenue per hectare. Bezabih et al., (2014a, 2014b) assessed the impact of weather/climate change measures on households' agricultural productivity measured in terms of crop revenue in Ethiopia. They used four waves of survey data, combined with interpolated daily temperature and monthly rainfall data from meteorological stations. Their findings show that temperature effects were distinctly non-linear, but only when the weather measures were combined with the extreme ends of the distribution of climate measures. In addition, they report that contrary to expectations for rain-fed agriculture rainfall generally had a less important role to play as compared to temperature.

2.2 An Overview of Climatic Conditions in Ethiopia

Ethiopia is characterized by diverse climatic conditions. The country's climate is largely determined by the seasonal migration of the inter-tropical convergence zone and a complex topography (NMA, 2001). One can identify three distinct rainfall regimes in Ethiopia classified according to annual distributional patterns. The southwest and western areas of the country are characterized by a uni-modal rainfall pattern, the central, eastern and north-eastern parts exhibit a quasi bi-modal pattern and the south and south-eastern areas a distinct bi-modal rainfall pattern (the World Bank, 2006). Mean annual rainfall ranges from about 2,000 mm over some areas in the southwest to less than 250mmover the Afar lowlands in the northeast and Ogaden in the southeast while mean annual temperature varies from about 10°C over the highlands of the northwest, central and southeast areas to about 35°C on the north-eastern edges. The country's climate is characterized by a history of extremes such as droughts and floods, increasing temperature trends and a decreasing trend in rainfall with increasing variability (Demeke et al., 2011). Annual average minimum temperature has been increasing by about 0.25°C every 10 years and the maximum by 0.1°C every decade. Despite ample groundwater and surface water resources, agriculture in Ethiopia is largely rain-fed. As a result, rainfall is considered the most important climatic element determining the performance of Ethiopian agriculture and hence its broad economy. Moreover, the rain-fed nature of agriculture underlines the importance of the timing and amount of rainfall in the country.

2.3 Agro-Ecological Classifications in Ethiopia

Ethiopia is characterized by a diverse topography and various atmospheric systems that result in varying climatic conditions. According to NMA (1996) the climatic conditions in the country can be divided into 11 climatic zones (CZs), broadly categorized as dry climate, tropical rainy climate and temperate rainy climate. These climatic conditions are directly related to the country's ecological conditions. Most importantly, the varying topography across the country and the different atmospheric circulation patterns determine rainfall and temperature patterns across CZs. Average temperature, distribution of annual rainfall and the length of the crop growing period substantially vary across the different CZs. Hence, based on the favorability of climatic and ecological conditions for agricultural production activities, MoA (2000) has broadly classified the country into five major AEZs -- desert, lowland, midland, highland and upper highland AEZs (Table 3.2). Further, based on homogeneity in terms of basic ecological elements of climate, physiography, soil, vegetation, land use, farming systems and animal production it has also classified the major AEZs into 18 agro-ecological sub-zones.

Table 3.2 Classification of AEZs in Ethiopia

AEZs	Average-annual Rainfall(mm)	Altitude(meters)	Average-annual Temperature(°C)	Length of growing Period(days)
Upper-highland	1,200-2,200	> 3,200	< 11.5	211-365
Highland	900-1,200	2,300-3,200	11.5-17.5	121-210
Midland	800-900	1,500-2,300	17.5-20.0	91-120
Lowland	200-800	500-1,500	20.0-27.5	46-90
Desert	< 200	< 500	> 27.5	0-45

Source: MoA (2000).

Farmers associations (FAs) selected for this essay also varied in the range of their agro-climatic conditions which enabled us to classify them into three AEZs and six agro-ecological sub-zones (AESZs) (Table 3.3). Accordingly, one FA was categorized as lowland AEZ, three were categorized as midland AEZs and four were classified as highland AEZs.

Table 3.3 Classification of the study area into AEZs and AESZs

Survey sites/FA	Region/ District	Average Rainfall(mm)	Altitude(m)	Average Temp.(°C)	Agro-ecological sub-zones (AESZs)	AEZs
Faji	Amhara/DB	77.8	2,750	13.24	Wet cool highland	High-land
Kara	Amhara/DB	77.8	2,750	13.24		
Milki	Amhara/DB	77.8	2,750	13.24		
Oda	Oromia/Tiyo	70.16	2,211	17.23	Cool highland	
Sirba	Oromia /Ada'a	92.40	1,763	20.16	Sub moist cool mid land	Mid-land
Turufe	Oro/Shashamane	65.26	1,937	17.51	Dry warm midland	
Somodo	Oromia /Jimma	139.63	1,718	20.00	Wet moist cool midland	
Koro	Oromia/Dodota	62.65	1,351	22.93	Hot to warm, sub moist lowland	Low-land

Source Author's classification

Accordingly, in the study area the midland AEZs covered the largest percentage (45.87 per cent), followed by the highland AEZs (31.55 per cent) and lowland AEZs (22.57 per cent). This AEZ classification of the study area may allow inter-regional comparisons of our results. Moreover, the central and most of the eastern half of the country that includes our study area have two rainy seasons (locally known as the Kiremt (summer) and the Belg (spring) seasons) and one dry season. The average duration of each season and the amount of rainfall and temperature varies from season to season and also geographically. The spring (Belg) season extends from March to May and is known as the short (minor) rainy season for most of Ethiopia, while the summer (Kiremt) season, which extends from June to September is known as the long or the main (major) rainy season. The dry season, Bega (winter), normally occurs between October and January. The annual weather distribution over the study region shows two peaks corresponding to the two rainy seasons, separated by a relatively short 'dry' period.

Further, depending on the time of crop harvest, there are two harvesting periods or seasons in Ethiopia (locally known as the Meher and the Belg cropping seasons). The Meher (main) cropping season is a season for any temporary crop harvested between September and February and such a crop is considered as Meher season crop, while the Belg cropping season is for any temporary crop harvested between March and August and such a crop is considered to be a Belg season crop (CSA, 2014). In Ethiopia crop production in the Meher season accounts for 90-95 per cent of the total annual production while the Belg season accounts for only 5-10 per cent of the total annual production (CSA, 2014). The failure of seasonal rains poses risks of droughts which reduce households' farm production by up to 90 per cent (the World Bank, 2003) though the severity, occurrence and frequency of droughts vary across the country. Thus, understanding annual and seasonal weather factors in different parts of the country or in different AEZs helps assess their impact on cereal productivity in different seasons, which also enables us to associate weather effects and yield data with appropriate seasons.

3. Method and Data

3.1. Theoretical Approach

Agricultural crop production requires farmers to produce the maximum output for a given level of possible input use. However, farmers' ability to produce efficiently often depends on production risks (variations in weather conditions), the production environment (operational conditions and practices) and farm-specific characteristics (technology selection or managerial practices) that could in turn lead agricultural production and productivity trends to fluctuate over time. Modeling the effects of agricultural inputs on crop production is not as straightforward as the standard production function (for example, CDPF) suggests. The manner in which certain inputs such as damage control inputs, contextual variables (that characterize operational conditions and practices) and production risk factors enter the production function has led people to question the conventional Cobb-Douglas specification. In some studies, inputs are presumed to directly increase potential yields as in CDPF. However, several studies reveal that inputs (for example, damage control inputs) do not directly increase potential yields but rather reduce damage to potential yields. Thus, productivity assessment from such different conditioned production factors/inputs is not as straightforward as that from direct (yield enhancing) inputs.

Lichtenberg and Zilberman (1986) were the first to propose a model for the special nature of damage control inputs as damage-abating inputs (such as pesticides) rather than as a crop yield-increasing inputs(like fertilizers) using a built-in damage control function. Subsequently, there has been some debate about the appropriate way to model productivity assessment in agriculture under different operational and risk conditions and practices. Consequently, many studies adapted this study by using a different functional form for the production function and unique estimation procedures noting the importance of such factors including weather variables in both the production and damage abatement functions, in impact and productivity assessment.

Their argument can be used to assess the impact of weather variations, agro-ecological and households' characteristics on crop productivity. For example, a strategy such as increased irrigation or considering weather factors such as changing temperatures or even agro-ecological characteristics like altitude and household characteristics like the age or educational level of the household head cannot enter the production function directly, though they have a bearing on the level of production. In the weather/climate change setting, this calls for specifying weather factors and agro-ecological factors alongside the usual production function.

Lichtenberg and Zilberman (1986) modeled the damage control function with a separable structure as:

$$(1) \qquad y = F\left\{ x^D, g(x^P, Z) \right\}$$

where, x^D is vector of direct inputs, x^P is vector of damage control inputs and Z is vector of damage factors.

Assuming the same argument in a climate change setting using the formulations of Lichtenberg and Zilberman (1986) and Kuosmanen et al., (2006) we assume that weather factors, farm household characteristics and agro-ecological factors influence cereal yields but not in the same manner as direct inputs. Hence, we hypothesize that cereal productivity is subject to factors such as direct factors of production, weather factors, farm household demographic and/or socioeconomic characteristics and agro-ecological factors and can be modeled as a composed function of a conventional production function and a function of non-conventional factors of production with a separable structure.

Assume that $i = (1, \dots, N)$ farm households operating in time periods denoted by t = (1, …, T) using a technology sub-set Γ denoted by $X^D = (x_1^D, ..., x) \in \Re^{N+}$ vector of direct inputs, used to produce a non-negative vector of farm outputs denoted by $Y = (y_1, ..., y_m) \in \Re^{M+}$.

In a changing climate with variable weather patterns, agricultural households with heterogeneous household demographic and/or socioeconomic characteristics denoted by the vector $Z = (z_1, ..., z_r) \in \Re^{R+}$; the production risks facing farmers due to extreme conditions of variability in weather factors denoted by the vector $W = (w_1, ..., w_s) \in \Re^{S+}$. These farmers also operate in certain agro-ecological zones which have a range of climatic conditions (rainfall, temperature and elevation) denoted by the vector $E = (e_1, ..., e_m) \in \Re^{D+}$.

Hence, under our assumption cereal crop productivity can be modeled as:

(2) $$Y = F\{ X^D, g(Z, W, E)\}$$

Assuming multiplicative separability of the weather factors, farm-household characteristics and agro-ecological factors from production activities (Kuosmanen et al., 2006), the function F can be equivalently expressed as:

(3) $$Y = f(X^D) \times g(Z, W, E)$$

where, f is a function of vector ***X*** consists of conventional, directly yield-enhancing inputs and g is a function of vectors Z, W and E consists of indirect factors of production. In this formulation the function *f* (**.**), will have a CDPF functional form. However, it may be the lack of appropriate functional form for the *g* (**.**) function in literature, though several cumulative distribution functions such as logistic, Weibull and exponential functions are available. This essay uses the exponential functional form for the *g* (**.**) function as has been used in most empirical work and it generally represents weather factors well and tends to be more flexible (Shankar and Thirtle, 2005).

Further, as Carpentier and Weaver (1997) have pointed out, for the requirements of multiplicative separability we assumed: (a) function f(.) to exhibit constant returns to scale; and (b) the influence of function g(.) as independent of the mixture of direct inputs f(.). But Kuosmanen et al., (2006) were able to demonstrate that this condition does not imply that f(.) and g(.) have no interdependencies or have no substitution possibilities or their marginal products will be independent. Extending this to a climate change setting, multiplicative separability does not imply that direct inputs, weather factors and agro-ecological characteristics have no interdependencies. Hence, based on these theoretical and conceptual approaches defining f(.) and g(.) functions as:

(4) $$f(.) = \beta_0 \prod X_{it}{}^{\beta} \;\; and \;\; g(.) = \exp\left(\sum W_{it}{}^{\delta} + \sum Z_{it}^{\eta} + \sum E_i^{\alpha} \right);$$

We reformulate Equation 3in a panel data context as:

(5) $$Y_{it} = \beta_0 \prod X_{it}{}^{\beta} \times \left[\exp\left(\sum W_{it}{}^{\delta} + \sum Z_{it}^{\eta} + \sum E_i^{\alpha} \right) \right] \times \exp^{\varepsilon_{it}}$$

where, β, δ, α and η represent the regression coefficient for the respective variables to be estimated and ε_{it} is the composite error term. All other variables maintain their previous definitions.

3.2 Empirical Model's Specifications

For empirical applications after including major variables (weather and production factors) and non-climatic factors (farm household demographic and socioeconomic characteristics, agro-ecological factors and the trend) in Equation 5, we specify the farm household-specific cereal productivity model as:

$$(6) \qquad Y_{it} = \beta_0 \prod X_{it}{}^{\beta} \times \left[\exp\left(\sum W_{i(t-1)}^{\delta} + \sum Z_{it}^{\eta} + \sum E_i^{\alpha} + T_t{}^{\mu} \right) \right] \times \exp^{\varepsilon_{it}}$$

Equation 6 can be transformed into a logarithmic form to obtain the following log-linear equation:

$$(7) \qquad \ln Y_{it} = \beta_0 + \sum_{j=1}^{7} \beta_j \ln X_{it} + \sum_{h=1}^{16} \delta_h W_{i(t-1)} + \sum_{n=1}^{6} \eta_n Z_{it} + \sum_{k=1}^{2} \alpha_k E_i + \mu_t T_t + \mu_{tt} T_t^2 + \varepsilon_{it}$$

where, *ln* is the natural logarithm; $i \in (1,2,...,N)$ is an index for farm household I; and $t \in (1,2,...,T)$ represents time period t. y is farm household-level total cereal production in monetary value per unit land; X includes the j^th direct input quantity for the i^th farmer at time period t; and *Z* includes the household's demographic and socioeconomic characteristics. *W* includes annual and seasonal weather factors at time *(t−1)*. *E* includes a set of regional dummy variables; T is a trend–the production years. Finally, ε_{it} is the composite error term decomposed into $\varepsilon_{it} = \alpha_i + u_{it}$; a normally distributed is a time-varying random shock $u_{it} \sim N(0, \sigma_u{}^2)$ and an unobserved time-invariant farm household-specific effect, (α_i). β, δ, α, η and μ represent regression coefficients for the respective variables to be estimated.

3.3. Estimation Methods

The model in Equation 7 is similar to standard panel data models. It uses the panel feature of the data via α_i, which is a time-invariant household-specific effect. This time-invariant attributes of farm-households may include some unobservable household-specific heterogeneity such as a farmer's instinctive ability unrelated to the production process which affects output. This model can be estimated assuming that either α_i is a fixed parameter - if the unobserved term is freely correlated with the independent variables (x_{it}) that directly influence the dependent variable (the fixed-effects (FE) model) or a random variable if it is uncorrelated with x_{it} (the random-effects (RE) model). Hence, we estimated the FE-model using the fixed-effects (within) estimator, which allows us to address the issue of endogeneity and time-invariant individual heterogeneity which is important in an analysis of farm productivity. We also estimated the RE model though this model tends to be avoided by economists and other social scientists due to its strong, often unrealistic assumption and issues of bias and uncertainty (Hausmann and Taylor, 1981).

In our model, the dependent variable and direct input variables are included in their logarithmic values to provide convenient interpretations and to reduce heterogeneity of the variance of production. Other explanatory variables enter the equation in a linear fashion. Hence, we interpreted for variables using elasticities as we used the log-linear functional form of the model's specification. The coefficients reflect percentage change in cereal productivity in response to percentage changes in respective inputs. However, the calculation of elasticities depends on the way in which the explanatory variables were specified (Nisrane et al., 2011). For those specified in logarithmic form, their coefficients themselves are the elasticities and as such were directly interpretable. For those that entered the equation in a linear fashion their coefficient estimates do not represent elasticity; instead they represent change in the logarithm of the dependent variable for a unit change in the respective inputs. Hence, for these variables, $\beta_j = \partial \ln Y_{it} / \partial X_j$, and the elasticity of the value of the dependent variable with respect to these inputs is calculated as $E_{YX} = (\partial \ln Y_{it} / \partial X_{it}) \times X_{it}$ where, Y_{it} is cereal productivity, and X_{it} is mean value of input X and these entered the equation linearly. For the dummy variables, $\beta_j = \partial \ln Y_{it} / \partial X_j$ is not defined because it is discontinuous. However, Nisrane et al., (2011) show elasticity with respect to those dummy variables given by $E_{YX_{DV}} = Exp(\beta_{DV}) - 1$, where, X_{DV} represents the dummy variable and β_{DV} is its estimated coefficient.

3.4. The Data, Study Area and Variables

This study employed a 4-round panel dataset commonly called the Ethiopian Rural Household Survey (ERHS) collected from randomly selected farm households in rural Ethiopia in 1999, 2004, 2009 and 2015. Originally, the earlier waves of the ERHS were conducted in collaboration with the Department of Economics, Addis Ababa University (AAU) and the International Food Policy Research Institute. Data collection started in 1989 in seven study sites. The 1989 survey was expanded in 1994 by incorporating other survey sites in different regions of the country. From 1994 onwards, data collection has been done in a panel framework. The number of study sites has increased to 15 with the resulting sample size totaling 1,477 farm households. The newly included study villages were selected to represent the country's diverse farming systems. Before a household was chosen, a numbered list of all households was developed with the help of local FA authorities. Once the list had been constructed, stratified random sampling was done to select sample households in each village whereby in each study site the sample size was proportionate to the population, resulting in a self-weighing sample.

The last round was extended from the original sample by forming a sub-sample of the original sample covering eight FAs following a similar strategy. This comprised of 503 farm households and was conducted by this researcher in 2015 with financial support from the Environment for Development (EfD) initiative at the University of Gothenburg, Sweden. The survey sites included FAs in Amhara and Oromia regional states; these are regions that represent the largest proportion of the predominantly settled farmers in the country. The eight FAs were selected to represent major cereal producing areas that may represent different AEZs in the country. These FAs are characterized by a mixed-farming system. The content of the questionnaire was extracted from ERHS and focused only on those parts which were required for the intended study.

The dataset was comprehensive, addressed farm households' demographic and socioeconomic characteristics; production inputs and output; and access to institutions. Moreover, important secondary data needed for the study like geographical location, elevation and metrological data on weather variables of FAs was obtained from the Ethiopian Meteorology Authority. The metrological dataset includes daily observations of rainfall and data on maximum and minimum temperatures collected in stations close to the study villages in 1994-2015.Consequently, this study used four (1999, 2004, 2009 and 2015) rounds of data forming 446 panel households consisting of 1,648 observations that were surveyed from 1999 onwards. The four rounds were selected to allow for even time spacing and covering approximately similar time frames. The 1994 survey was excluded as it did not have most of the important variables for the analysis.

Variables used in the analysis

We used monetary measures of some inputs and output and made their weighted aggregations at the farm household level to avoid the problem of indivisibility of input and output variables. The dependent variable used in the analysis is total cereal production value per unit land for each farm household. In our model, we hypothesize that direct factors of production, weather factors, farm-household and agro-ecological characteristics affect cereal productivity. Accordingly, we include as explanatory variable the ***direct factors of production.*** These include cereal planted land quality (measured in indices); labor employed measured in man-day units (MDUs); the amount of fertilizers used measured in kilogram; machinery implements used measured in monetary equivalents; livestock ownership measured in tropical livestock units (TLUs) as a proxy for wealth and livestock asset-endowments; agro-chemicals measured in monetary equivalents (pesticides, herbicides and insecticides); oxen as animal draft power measured in number of oxen (oxen are mainly used in traditional farming during land preparation and the harvesting period); and land quality measured in an index (this variable is developed following (Nisrane et al., 2011) to represent the land quality of the plots cultivated by households which was proxied by an index as an indicator for the land or soil quality using the information on the slope type and the fertility of the land (plots).

Farm-household demographic and socioeconomic characteristics include age of the household head; education of the household head measured in years of schooling; household's family size, the number of plots that the farmers were cultivating, which was used as a proxy for measuring farmland fragmentation; and agricultural advisory services as public support to farmers represented by the participation of farmers in governmental agricultural extension services which was 1 if the household participated and 0 otherwise.

Weather variables include lagged annual and seasonal weather measures - averages of rainfall and temperature observations for a year prior to the corresponding survey year and their squared terms. For this monthly weather observations (rainfall and temperature variables**)** in a year prior to the corresponding survey years were averaged for each year to construct the average weather measures. In addition, given the seasonality of the rainfall and cropping patterns in Ethiopian agriculture, further aggregation of precipitation and temperature distribution was done for the pre-planting or land preparation period (spring), the period of planting and growing (summer) and the period of maturing/harvesting (fall or autumn), instead of an aggregate growing season used in much of the literature. In this essay the spring season includes the months between March and May, the summer season includes the months between June and September, while the fall or autumn season includes the months between October and December. We also considered the cereal crop only from the Meher cropping season and did not include the weather observations for the period (January to February) in our seasonal weather measures. Similar approaches have been followed in previous studies (see Bezabih et al., 2014). Moreover, the inclusion of seasonal weather variables matched the production cycle with rainfall and temperature fairly well in the pre-planting or land preparation (spring) period, planting and growing (summer) period and maturing/harvesting (fall or autumn) period of the Meher cropping season or for the Meher cereal crop.

The ***AEZs' dummy variables*** include the AEZs' characteristics to represent location-specific time-invariant factors to account for productivity differences that could result from the overall agro-ecological factors that could not be captured by other variables in the model. Finally time ***trend,*** in which the time trend and its square is used as a proxy for technical change in crop production due to technological changes over time. The linear term captures the direction of the change and those effects that we cannot measure but which nonetheless affect farm output (for example, input prices), while the squared term captures the non-linear shift in the production function over time.

3.5 Descriptive Analysis

Table 3.4 presents the descriptive statistics of the variables used in the regressions including the relevant temperature and rainfall measures. As shown in Table 3.4, on average the farmers were able to produce 19.5 quintals of cereals during 1999-2015. Observing this year by year (as shown in Table 3.4 and Figure 3.1a) the mean of cereal output and productivity both in quantity and monetary value terms increased over time during the study period. Mean of output was about 12.6 quintals in 1999 which rose steadily to 30.2 quintals in 2014. In terms of yield captured in quintals per acreage, farms/households had a mean of 9.6 units in 1999 which rose to 21.2 units in 2015.

Table 3.4 Summery statistics of the variables used in the regressions (NT = 1,648)

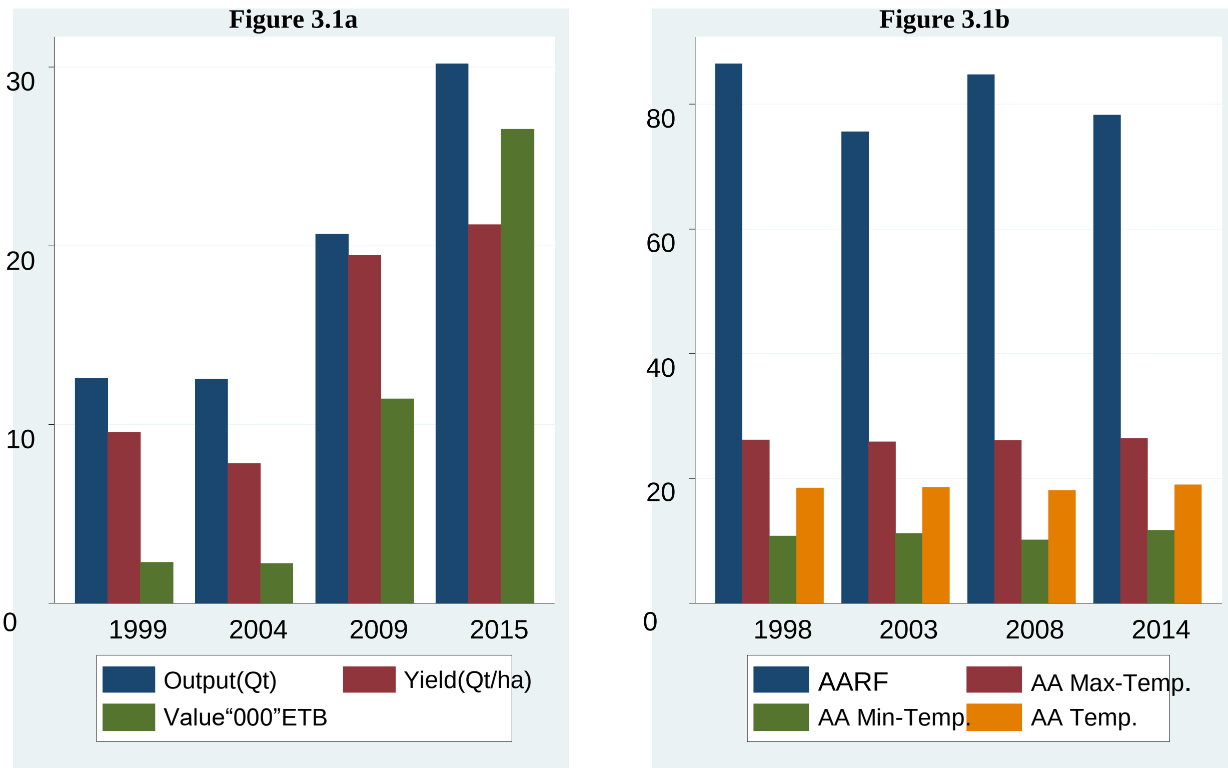
Variable	Mean	Std. Dev.	Min	Max
Output produced(kg)	1,952.251	2,681.805	34.000	51,100.000
Yield(Q/ha)	1308.933	1878.037	8.588	50,000.000
Fertilizers used(kg)	116.100	138.850	0.080	1,400.000
Agro-chemicals(ETB)	133.900	447.170	0.010	8,560.000
Farm labor (MEU)	342.620	714.210	3.000	8,333.880
Machinery(ETB)	336.690	1,775.800	0.500	36,540.000
Livestock units (TLUs)	6.490	5.930	0.001	58.800
Number of ploughing oxen	1.770	1.330	0.010	9.000
Cultivated land area (HEC)	1.750	1.280	0.020	11.000
Household size	5.830	2.670	1.000	18.000
Number of plots cultivated	3.620	2.440	1.000	16.000
Land quality (index)	2.372	4.320	1.000	9.000
Household head's age(years)	51.169	15.359	18.000	103.000
Head Educ.(years)	4.958131	6.320335	1.000	16.000
Weather variables				
Annual average rainfall (PRECIP)(mm)	82.055	26.881	47.467	145.958
Annual average minimum temp.(°C)	10.921	2.983	6.358	17.217
Annual average maximum temp.(°C)	26.137	4.134	19.908	33.014
Annual average temp.(°C)	18.483	3.446	13.158	23.958
Spring season precipitation (mm)	66.091	39.433	20.800	186.600
Summer season precipitation (mm)	171.092	61.142	84.933	324.133
Fall season precipitation (mm)	57.042	28.717	18.950	125.700
Spring season temp.(°C)	17.647	3.908	10.950	23.683
Summer season temp.(°C)	18.743	3.450	13.200	24.588
Fall season temp.(°C)	17.674	3.955	10.650	24.583

Source: Author's calculations.

This shows an average annual growth rate of about 5 per cent. For such production, on average farmers used 342.7 man-day units (MDUs) of labor, 188 kilograms of seeds, 116.1 kilograms of fertilizers and spent 133.9 ETB for agro-chemicals and cultivated 1.8 hectares of cereal farmland per farm/household. The average land quality index was 2.4, ranging between one and nine. Land quality was proxied by an index as an indicator for the land or soil quality using the information on the slope type and fertility of the land (plots) cultivated by the households. The computed index is a combination of the assigned values of the quality indicators of the slope type and fertility of the land (plots). As to the computational orientation of these indices, the closer the index is to one, the higher is the quality of land, while the closer the index is to nine, the lower is the quality of the land.

The number of plots cultivated by farmers which is also used as a proxy to measure land fragmentation among subsistent smallholders averaged 3.6 with a maximum of 16 plots. Average livestock ownership was 6.5 TLUs, while oxen ownership was 1.8 or almost two oxen per farm/household. A majority of the farmers/households were male-headed (1,262 or 76.58 per cent). On average, the household heads were 51.2 years old and had an average of 5 years of schooling. The farmers' family size averaged six ranging from one to 18 members. In addition, 631(38.29 per cent) farmers reported contact with agricultural extension agents but very little contact per month.

As shown in Table 3.4, average annual rainfall was 82.06 mm with a maximum and minimum of 145.958 and 47.467mm respectively. As expected, the summer season, which is the wettest, received average precipitation of 171.092 mm, while the average precipitation in the spring and fall seasons was 66.091mm and 57.042mm respectively. Average annual temperature was 18.425°C, with the average maximum and minimum temperature being 26.137 and 10.921°C respectively. The summer season, which is the warmest, on average had a temperature of 18.743°C, while the spring and fall seasons had almost similar temperature levels at17.647°C and 17.674°C respectively. The weather observations show a significant declining trend in annual average rainfall and warming trends in temperature variables. One can also notice that average rainfall distribution declined over time at a rate of 0.029mm annually and average temperature distribution increased at rate of 0.009°C annually during the study period.



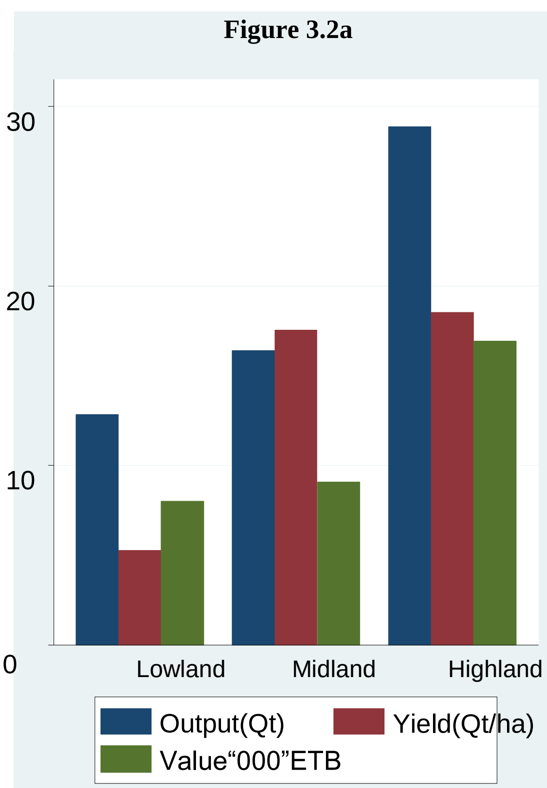
Source: Author's computations.

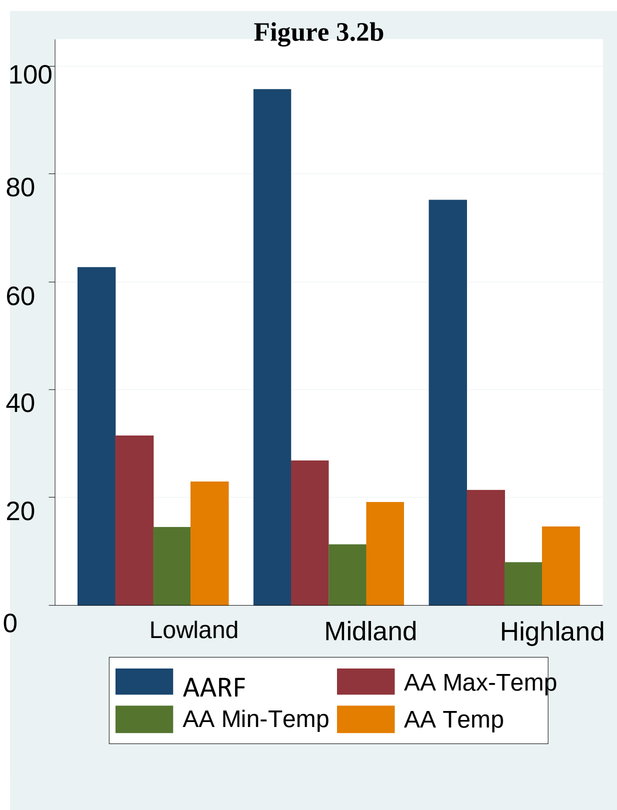
Figure 3.1 Average output, yield and weather variables (by years)

As shown in Figure 1b, during the study period the average annual rainfall was 81.77mm and the average annual temperature was 18.53°C with the maximum temperature being 26.13°C and the minimum temperature being 10.92°C. Average annual rainfall distribution declined over time as the mean annual rainfall in 1998 was 86.5mm which showed a slight decline in 2014 to 78.32mm whereas the distribution of annual average temperature increased over time -- mean average annual temperature in 1998 was 18.46°C which showed a slight increase to almost 19.02°Cin 2014. In general, the descriptive summary shows that there were significant weather variations during the study period with a decline in annual rainfall by almost 8.18mm on average and an increase in annual temperature by 0.56°C, that is rainfall declined by 2.73mm and the temperature increased by 0.19°C per year.

A comparison of AEZs

As shown in Figure 3.2a, as one moves from lowland to highland AEZs, both cereal output and yield increase. The weather variables across AEZs (Figure 3.2b) show that mean average annual rainfall and maximum and minimum temperatures in the lowland AEZs were 62.65mm, 31.44°C and 14.43°C respectively. Similarly, mean average annual rainfall and maximum and minimum temperatures in midland ACZs were 95.73mm, 26.82°C and11.28°C respectively while these were 78.7mm, 20.0°C and 6.1°C respectively in the highland AEZs.





Source: Author’s computations.

Figure 3.2 Average output, yield and weather variables (by AEZs)

On the other hand, when we see cereal production, yield and weather variables over the panel years in each AEZ we find that average output and yield rose steadily in the panel years in each AEZ. This shows output and yield increased over time in all AEZs. However, average annual weather variables per year in each AEZ were not uniform; for example, rainfall declined in midland and highland AEZs, while their temperatures increased; in lowland AEZs these trends were the opposite.

4. EMPIRICAL RESULTs AND DISCUSSION

4.1. Estimation and Econometric Diagnoses

Table 3.5 presents parameter estimates from fixed-effects and random-effects models. The FE model was used to capture any time-invariant unobserved farm household-specific heterogeneity effect and the RE model to capture the influence of agro-ecological effects. Several estimation diagnoses were also performed. To check for multicollinearity and confounded effects among the explanatory variables, this study estimated the pair-wise correlation coefficients among the variables. These correlation coefficients verified the following explanatory variables: fertilizers, agro-chemicals, livestock, machinery and oxen were positively and highly correlated with cereal productivity, while it was negatively correlated with labor, planted area, age and temperature. The remaining variables were positively correlated with cereal productivity. Only a pair of weather variables showed a correlation higher than 0.50 indicating serious multicollinearity and possible confounded effects. The remaining pairs had low pair-wise correlations with each other showing that there was very weak collinearity between them. This implies the almost non-existence of multicollinearity problem.

The study used the Hausman-Wu procedure (Hausman 1978; Wu 1973) to test for the existence of an endogeneity problem and the results are not significant in the test equation, indicating that there was no endogenous variable. The Ramsey (1969) regression specification error test showed (prob > F = 0.1136) indicating that there were no omitted variables; the Breusch-Pagan LM test for random effects revealed that there was no unobserved household heterogeneity as the p-value was greater than 0.05. We also performed the Hausman test (Wooldridge, 2002) to check the appropriateness of the FEM and the RE model's estimates. The results show that the fixed effects estimation was more efficient as compared to the random effects estimation. Accordingly, our report is primarily based on fixed effects results. We used the robust standard errors to diminish the heteroscedasticity problem.

4.2. Analysis of Estimation Results

Table 3.5 presents the regression results of the panel dataset. In general, it can be seen from the table that almost all parameter estimates from either of the models have the expected signs and are significantly different from zero at the 5 per cent level or below. The FEM estimates differ slightly from the RE estimates with some improvements and the parameters are still significant. Hence, after assessing the models' estimates we refer to the fixed-effects results, except for the agro-climatic dummy variables that were used for identifying the impact of agro-ecological differences for interpretation. As expected, most of the direct production inputs and household characteristics impacted cereal productivity in the right way and were significant in the model. As shown in Table 3.5 inputs like agro-chemicals, livestock ownership, number of plots, education and agricultural extension services significantly enhanced cereal productivity. On the other hand, cereal sown land size and head's age negatively and significantly influenced cereal productivity.

The estimated coefficients of agro-chemicals' showed a positive enhancement on cereal productivity significantly at 1 per cent. Its elasticity implies that an increase in agro-chemical use by 1 unit increased cereal productivity by 0.037 per cent. Consistent with our expectations, livestock ownership was positively and significantly associated with cereal productivity at the 1 per cent level, implying that the more livestock a household had the better its cereal productivity. These results are in line with the findings of several other empirical works (Nisrane et al., 2011). The elasticity of this variable indicates that an increase in livestock ownership by 1 per cent increased productivity by 0.125 per cent. The positive sign indicates that the availability of this asset was essential in several respects. For instance, farmers with more livestock units which can readily be converted to money can buy modern farm inputs such as seeds, fertilizers and other chemicals than those who own fewer livestock units. Moreover, apart from smoothing their incomes, families with more animals are more likely to have larger protein intakes than those with fewer animals which helps improve their working efficiency. They also use dung cakes to fertilize homesteads. Besides, pack animals are used for timely transportation of the crops to a threshing point. Since threshing is conducted using animal power, the availability of livestock, especially during peak periods is vital for reducing post-harvest losses.

We included the number of plots that the farmers cultivated in the analysis to assess the effect of dissected plots for a given size of cultivated land on farming productivity; this was positively and significantly associated with cereal productivity at the 1 per cent level. The result implies that for a given amount of land for crop cultivation, an increase in the number of plots for cultivation led to increased cereal productivity. The positive sign of this coefficient may also represent the reduced risk that different plots provide if the plots are sufficiently disbursed so that farmers face different degrees of weather-induced variations and mineral content. Moreover, the result can be explained in terms of access to farmland and that farmers with more plots are likely to adopt innovations because they may be willing and able to bear more risks than their counterparts and may have preferential access to farm inputs which enables them to improve the level of their crop production and productivity. Its elasticity indicates that an increase in the number of plots that farmers cultivated by 1 per cent will increase cereal output and hence increases productivity by more than 0.023 per cent.

Table 3.5 Parameter Estimates: Impact of climatic and non-climatic variables on cereal productivity (NT = 1,648)

Explanatory-variables	Dependent-variable: Cereal yield				
	Random-effect		Fixed-effect		
	Coefficients	Std. Err.(Robust)	Coefficients	Std. Err.(Robust)	Elasticities
Fertilizers	0.044***	0.015	0.020	0.017	0.020
Agrochemicals	0.039***	0.012	0.037***	0.013	0.037
Labor	0.042**	0.023	0.024	0.025	0.024
Machinery	0.025*	0.015	0.019	0.017	0.019
Livestock	0.191***	0.029	0.125***	0.037	0.125
Land quality	-0.284***	0.059	-0.303***	0.062	-0.303
Oxen	0.157***	0.053	0.091	0.063	0.091
Number of plots	0.069***	0.010	0.054***	0.012	0.023
Head's-age	-0.020**	0.010	-0.025**	0.011	-0.149
Age-squared	0.016*	0.009	0.019*	0.010	0.065
Family-size	0.008	0.009	0.015	0.011	0.010
Head's-Education	0.002	0.004	0.007*	0.004	0.004
Agricultural Ext. Services	0.113**	0.047	0.099*	0.057	0.406
Annual precipitation	0.043	0.039	0.281***	0.054	2.501
Annual precipitation^2	-0.015	0.013	-0.076***	0.017	-0.541
Summer precipitation	-0.031***	0.008	-0.017	0.013	-0.323
Summer precipitation^2	0.008***	0.002	-0.002	0.003	-0.077
Fall precipitation	-0.106***	0.021	-0.016	0.028	-0.125
Fall precipitation^2	0.06***	0.012	0.009	0.016	0.061
Spring precipitation	0.017*	0.009	-0.052***	0.012	-0.313
Spring precipitation^2	-0.009*	0.004	-0.003	0.007	-0.012
Annual temperature	-2.468	1.832	-12.700***	2.830	-27.764
Annual temperature^2	2.574	4.790	28.950***	6.907	12.029
Summer temperature	1.011	0.912	-4.800***	1.091	-11.045
Summer temperature^2	-1.412	2.209	11.800***	2.606	5.412
Fall temperature	-5.218***	1.482	9.700***	2.273	20.142
Fall temperature^2	13.300***	3.437	-22.2***	5.358	-8.605
Spring temperature	8.343***	1.814	7.673***	2.370	17.772
Spring temperature^2	-15.400***	3.944	-18.100***	5.066	-8.419
Highland	5.136***	0.857			62.579

Midland	2.665***	0.487			5.284
Time	0.129***	0.010	0.078***	0.011	18.428
Time^2	-0.476***	0.109	-0.831***	0.210	
Constants	-281.800***	24.532	-152.80***	23.337	
F-statistic	Wald chi^2(32)=3151.26***		F(30, 445)=77.01***		
R-squared	Within=0.5931		Within=0.6121		
	between=0.6026		between=0.0096		
	overall=0.5968		overall=0.1174		

Note *: p<0.05; **: p<0.01; ***: p<0.001.

The regression results further indicate that the land quality of the plots had a negative significant impact at the 1 per cent level. Ceteris paribus its estimated elasticity shows that a decrease in average land quality by 1 per cent will decrease cereal productivity by 30.3 per cent. This result shows the crucial role that the responsible body needs to play in increasing the quality of arable land through improved farm management techniques. The result is similar to that in Nisrane et al., (2011) and Ayalew et al., (2014) using earlier data from the ERHS dataset.

Estimates of the educational levels of household heads show that education affected cereal productivity positively at the 5 per cent significance level. Its elasticity indicates that an increase in the educational level by 1 per cent will increase cereal productivity by 0.004 per cent. This result is in line with Battese and Coelli's (1995) result who hypothesized education to increase a household's ability to use existing technologies and have efficient management of production systems hence attaining higher productivity levels. Among the socioeconomic variables, access to agricultural extension services as public support to farmers had a significant positive impact at the 10 per cent level. The result reveals that increased access to extension services and more contacts with extension agents were associated with improved farming information, which is important for crop productivity. Thus, ceteris paribus, the corresponding elasticity shows that an increase in participation and number of contacts with extension agents could lead to a rise in cereal productivity by 0.406 per cent.

Age had a significant negative impact on cereal productivity at the 5 per cent level, while its square affected productivity positively at the 10 per cent significance level indicating that age had a non-linear relationship with crop productivity. This further indicates that older household heads were less productive as compared to younger ones. Moreover, the result can be explained in terms of crop production practices. The negative sign for the coefficient can be attributed to the unwillingness of older and more experienced households to use new techniques and modern inputs, whereas younger farmers by virtue of their greater opportunities to formal education, may be more skillful in their search for information and the application of new techniques (Hussain, 1989). This result can be supported by the result from the descriptive summary, as the age of the farmers ranged between 17 and 103 years with a mean of 51 years, implying that the farmers were relatively old, a condition that might affect productivity negatively. Its elasticity indicates that as a farmer gets old by 1 per cent, his cereal productivity will decline by 0.004 per cent, until a turning point is reached beyond which getting old by 1 per cent will increase productivity by 0.065 per cent.

Weather Variations' Effect on Yield

The effect of weather variability is as anticipated as climate related variables significantly affected cereal productivity. Linear and squared-term coefficients in both the models show that cereal productivity was generally sensitive to weather variables. The results reveal that most of the squared terms of the weather variables were significant annually and seasonally at the 1 per cent level, implying that weather variations had a non-linear effect on cereal productivity. When the coefficients of the quadratic terms are positive, the crop productivity function has a U-shape and will have an inverted U-shape when the quadratic term is negative. This shows that there is a known amount and time range of temperature and precipitation in which a crop grows best across the seasons and/or annually, although optimal weather factors vary from crop to crop (Mendelsohn et al., 1994). For example, this essay hypothesized that peak mean rainfall influenced crop productivity positively, that is, more rainfall increased the productivity of cereal crops. Expectedly, the results show that an increase in precipitation, particularly for annual mean rainfall, had a positive effect on crop productivity. However, this was up to a point and then production, hence productively started declining as shown by the coefficient of the squared term of annual rainfall. Similar explanations hold for the results of the other weather variables.

The results show that annual rainfall affected crop productivity positively, while its squared term had a negative effect both significantly at 1 per cent. This means that annual rainfall had a negative effect on cereal crops until a turning point was reached beyond which the value of rainfall had a positive impact. Its coefficient suggests that if annual rainfall was favorable (in terms of timeliness, amount and distribution), then households experienced a relatively better crop productivity condition. This result may be due to the fact that rainfall enhances crop productivity as it improves the soil's capacity and enables it to use the fertilizers and other inputs effectively (Tchale and Suaer, 2007). An analysis of the seasons shows that precipitation during the spring season affected cereal productivity negatively at 1the per cent significance level. Similarly, summer and fall seasons' precipitation affected cereal productivity negatively. The decrease in crop productivity with increasing summer precipitation indicates that the existing current level of precipitation was enough for planting. Reduction in crop productivity with an increase in precipitation during the fall season - the period commonly known as the harvesting season in the study area --is due to crops' reduced water requirements and consequently more precipitation damaging the crops (Deressa et al., 2009) during the harvesting season.

Contrary to annual precipitation, annual and summer season temperatures were associated negatively with cereal productivity. Moreover, the coefficients of the temperature variables had large values implying that temperature variations had a large impact on cereal productivity. The results show that annual and summer season temperatures affected cereal productivity negatively while their squared terms had positive effects, all significantly at 1 per cent. This may be due to an increase in average minimum temperature or decrease in average maximum temperature measured annually or during the crop growing season leading to a decline in crop productivity. These results are in line with those of Schlenkeret et al., (2006) who showed that the extreme end of the average temperature distribution was always harmful for crop growth irrespective of the type of crop. Our regression results also show that average temperature during fall and spring affected cereal productivity positively, while their squared terms had a negative effect at 1 per cent. The results suggest that an increase in temperature enhances cereal productivity during these seasons. During the fall season, a higher temperature is beneficial for harvesting. It is important to notice that most crops have finished their growing period by autumn, and a higher temperature quickly dries up the crops and facilitates harvesting so it has a positive effect on crop productivity (Mendelsohn and Dinar, 2003). In general, these findings confirm that weather variability is one of the critical 'drivers of crop productivity' in many African agrarian-households (the World Bank, 2006).

Marginal Effect Analysis of Weather Variables

Considering linear and squared terms the weather coefficients reveal that cereal productivity is generally sensitive to weather variations. However, their effect is not obviously determined simply by looking at the coefficients because the linear and the squared terms play a role; rather their effect can be interpreted based on their marginal-effects or elasticities (Kurukulasuriya and Mendelsohn, 2008). This is important for observing the overall effect of an infinitesimal change in weather variables on cereal productivity and for avoiding complexity of the analysis and its interpretations due to squared terms.

Following Lee et al., (2012) and denoting the weather variables as W, one can derive the marginal impacts (elasticities in our case) of the weather variables (W_i) on cereal productivity evaluated at the mean of that variable:

$$E\left[\frac{dY}{dW_i}\right] = E\left(\beta_{1i} + 2\beta_{2i}W_i\right) * E\left(W_i\right) = \left(\beta_{1i} + 2\beta_{2i}E(W_i)\right) * E\left(W_i\right) = \left(\beta_{1i} + 2\beta_{2i}\overline{W_i}\right) * \overline{W_i} \quad (8)$$

where, E is the expectations operator; $\beta_{1i}$and β_{2i} are the semi-elasticities of the linear and quadratic terms respectively. $E\left(W_i\right) = \overline{W_i}$, are mean values of the corresponding weather variable.

Table 3.6 Calculated elasticities of weather variables on cereal productivity

Variable	Annual	Summer	Fall	Spring
Precipitation	1.686***	-0.576	-0.041	-0.326***
Temperature	-23.330***	-8.953***	17.098***	14.476***

Note ***: p<0.001.

Table 3.6 shows elasticities of annual and seasonal weather variables, which show the effects of an increase in temperature by 1°C and precipitation by 1 mm per year/season on cereal productivity. The sign of the calculated elasticities of the precipitation variables indicates that a

1mm increase in annual precipitation had a positive effect, while seasonal precipitation had a negative effect on cereal productivity. On the other hand, an increase in annual and summer temperature decreased cereal productivity, while an increase in temperature during the fall and spring increased cereal productivity. Hence, as shown in Table 3.6, their elasticities suggest that any increase in average annual precipitation by 1 mm will increase cereal productivity levels by 1.686 per cent. Interpreting these results, the other way around a decrease in precipitation by 1 mm annually will lead to a decrease in cereal productivity by 1.686 per cent, all at 1 per cent; while a 1mm increase during the spring will lead to a decline in crop productivity by 0.326 per cent. The elasticities of temperature variables indicate that a 1°C increase in annual and summer temperatures could lead to a decrease in cereal productivity by 23.330 and 8.953 per cent respectively, while a 1°C increase in fall and spring temperatures will lead to an increase in cereal production and thus an increase in productivity by 17.098 and 14.476 per cent respectively, all at 1 per cent.

As expected, geographical differences affect cereal productivity positively at the 1 per cent level. Farming in midland or highland areas as compared to lowland areas contributed to an increase in productivity. This point to the importance of location-specific determinants of cereal productivity with households in the highland demonstrating higher productivity compared to those in the lowland. In line with the descriptive results, the corresponding computed coefficients show that cereal productivity increased in highland AEZs by 62.579 per cent and also increased in midland AEZs by 5.284 per cent. Therefore, more production with better productivity is likely to be at higher altitudes where rainfall and temperature are favorable for farm production.

Lastly, the results of the time-trend variable ---a proxy variable for technical change in cereal production-- positively impacted cereal productivity at 1 per cent. The linear term suggests that there is technological progress or upward shift in production between these time periods and the squared term indicates technical progress at a decreasing rate. Its calculated elasticity shows that there was an increase in cereal productivity by 18.428 per cent over the 15years implying that there were technical improvements among Ethiopian cereal farmers in 1999-2014.

5. Conclusion and Recommendations

A large body of literature demonstrates negative impacts of climate change and weather variations on crop production and productivity in developing countries. As climate change is likely to intensify high temperatures and low precipitation it's most dramatic impacts will be felt by smallholder and subsistence farmers. It is observed in Ethiopian cereal production that while for a majority of the cereals the productivity increase is due to increased use of physical inputs and governmental support, the gradual change in annual and seasonal weather factors in the last few decades has had a measurable effect on production and productivity. This essay evaluated the impacts of climatic/weather and non-climatic factors on cereal productivity and provided descriptive and econometrics analyses of their impacts on cereal productivity using a 4-round panel data from randomly selected rural farm households in Ethiopia covering the period 1999-

2014. Consistent with previous findings of productivity studies in SSA which primarily consider conventional agricultural production inputs and climate factors; our results confirm the importance and statistically strong dependence between most of the explanatory variables and cereal productivity.

The descriptive results show that cereal crop production and productivity increased over the period and in each AEZ. The average annual rainfall distribution declined, while average annual temperature increased in the study period. However, these trends were not uniform in the AEZs. The econometrics results indicate that inputs such agro-chemicals, livestock, number of plots, and participation in agricultural extension services significantly enhanced cereal productivity. On the other hand, the quality of cereal planted land and household head's age and educational level influenced cereal productivity negatively. Linear and squared weather variables' coefficients reveal that cereal productivity is generally sensitive to weather variations. Further, linear and squared estimates of weather variables -- annually and seasonally -- were found to be significant determinants of productivity, implying that climate had a non-linear effect on cereal productivity.

Average annual rainfall affected cereal productivity positively while its squared term had a significant negative effect. Its marginal effect suggests that an increase in average annual precipitation by 1mm will increase productivity by more than 1.69 per cent. Spring precipitation affected cereal productivity negatively while summer and fall precipitation affected it negatively. On the other hand, annual temperature affected cereal productivity negatively while its squared term had a positive effect. Its marginal effect suggests that a 1^{o}C increase in annual temperature could reduce productivity by 23.33 per cent. This may be due to an increase in average annual minimum or maximum temperatures during the crop growing season which in turn leads to a decline in cereal productivity. Further, fall and spring temperatures affected cereal productivity positively while summer season temperatures affected it negatively.

The results also show that geographical differences - a set of regional dummy variables -- considerably affected cereal productivity. This suggests the importance of location-specific determinants of cereal productivity with households in the highland demonstrating a higher position compared to those in the lowland. Therefore, more production is likely at higher altitudes where rainfall and temperature are favorable for cereal production. Lastly, estimates of the time-trend variables show a technological pro-regress but at a decreasing rate in cereal productivity over the period. These outcomes are important and can be used to inform the government on possible policy decisions such as where to emphasize when planning and promoting climate change adaptation strategies and ways to envisage better provision of extension services that are tailored to the peculiarities of the AEZs across the country. Thus, the study's results confirm that weather change contributes to lesser cereal productivity in Ethiopia. Having poverty and food-security implications, the study therefore recommends public policies geared at improving agricultural extension services, farmers' education, agricultural inputs supply and climate change adaptation strategies and policies that could meet farmers' needs and also be suitable for AEZs.

References

Addai, K.N. & V. Owusu (2014). Technical efficiency of maize farmers across various agro ecological zones of Ghana. *Journal of Agriculture & Environmental Sciences*, 3(1): 149-72.

African Development Bank (AfDB) (2016). *Federal Democratic Republic of Ethiopia: Country Strategy Paper-CSP*, 2016-20.

Ayalew Z. A, B. A. Alemu, and M. A. Hanjra (2014). Policies for Agricultural Productivity Growth and Poverty Reduction in Ethiopia. *World Development*, 59: 461–74.

Bamlaku B.A., E.A. Nuppenau, and H. Boland (2009). Technical Efficiency of Farming Systems across Agro Ecological Zones in Ethiopia: An Application of Stochastic Frontier Approach. *Agricultural Journal*, 4(4): 202-7.

Battese, G.E. and T.J. Coelli (1995). A Model for Technical Inefficiency in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20: 325-32.

Bezabih M., S. Di Falco, and M. Alemu (2014a). Is it the climate or the weather? Differential economic impacts of climatic factors in Ethiopia. Paper provided by Grantham Research Institute on Climate Change and the Environment in its series. GRI Working Paper No. 148.

Bezabih M., S. Di Falco, and M. Alemu (2014b). On the Impact of Weather Variability and Climate Change on Agriculture: Evidence from Ethiopia. Environment for Development and Resource for the Future. Discussion Paper series, 14-15.

Carpentier, A. and R.D. Weaver (1997). Damage Control Productivity: Why Econometrics Matters. *American Journal of Agricultural Economics*, 79: 47–61.

Central Statistical Agency (CSA) (2007). *Country Population and Housing Census Report-2007*. Addis Ababa: The Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development (MoFED).

Central Statistical Agency (CSA) (2014). *Agricultural sample survey(AgSS 2013-2014).Report on area and production of major crops, private peasant holdings, Meher season, Volume I.* Addis Ababa: The Federal Democratic Republic of Ethiopia (MoFED).

Demeke, A. B., K. Alwin, and Z. Manfred (2011). Using panel data to estimate the effect of rainfall shocks on smallholders' food security and vulnerability in rural Ethiopia. *Climatic Change*, 108:185–206.

Deressa T., R.M. Hassan, T. Alemu, M. Yesuf, and C. Ringler (2009). *Analyzing the Determinants of Farmers' Choice of Adaptation Methods and Perceptions of Climate Change in the Nile Basin of Ethiopia.* IFPRI.

Food and Agriculture Organization of the United Nations (FAO) (2009). *Food security and agricultural mitigation in developing countries: Options for capturing synergies*. Rome: FAO.

Guiteras, R. (2009). The impact of climate change on Indian Agriculture, Mimeo.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica*, 46: 1251-71.

Hausman, J. and W. Taylor (1981). Panel data and unobservable individual effects. *Econometrica,* 49 (6): 1377-98.

Hussain, S.S. (1989). Analysis of economic efficiency in Northern Pakistan: Estimation, a uses and policy implications, PhD dissertation, University of Illinois, Urbana-Champaign.

IPCC (2012). Managing the risks of extreme events and disasters to advance climate change adaptation; a special report of working groups i and ii of the IPCC. Technical report.

Kassahun, A. (2011). The Impact of Climate Variability on Crop Production in Ethiopia: Which Crop Is More Vulnerable to Rainfall Variability? Paper presented at the 9th International Conference of EEA, Addis Ababa, Ethiopia.

Kuosmanen, T., D. Pemsl, and J. Wesseler (2006). Specification and Estimation of Production Functions Involving Damage Control Inputs: A Two-stage, Semi-parametric Approach. *American Journal of Agricultural Economics,* 88(2): 499-511.

Kurukulasuriya, P. and R. Mendelsohn (2008). A Ricardian Analysis of the Impact of Climate Change on African Cropland. *African Journal of Agricultural and Resource Economics,* 2(1): 1-23.

Lee J., D. Nadolnyak, and V. Hartarska (2012). Impact of Climate Change on Agricultural Production in Asian Countries: Evidence from Panel Study, Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Birmingham.

Liangzhi, Y, M.W. Rosegrant, C. Fang, and S. Wood (2005). *Impact of Global Warming on Chinese Wheat Productivity, EPT Discussion Paper 143*. IFPRI.

Lichtenberg, E. and D. Zilberman (1986). The Econometrics of Damage Control: Why Specification Matters. *American Journal of Agricultural Economics,* 68: 261–73.

Mendelsohn, R. and A. Dinar (2003). Climate and rural income. Mimeo, School of Forestry and Environmental Studies, Yale University.

Mendelsohn, R., W. Nordhaus, and D. Shaw (1994). The impact of global warming on agriculture: A Ricardian analysis. *American Economic Review,* 84: 753–71.

Ministry of Agriculture (MoA) (2000). *Agro-ecological Zonation of Ethiopia.* Addis Ababa:The Federal Democratic Republic of Ethiopia, Ministry of Agriculture.

Ministry of Finance and Economic Development (MoFED) (2010). *Growth and Transformation Plan I,*volume 1. Addis Ababa: The Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development.

National Meteorological Agency (NMA) (1996). *Climate and Agro-Climatic Resources of Ethiopia, Meteorological Research Report Series, 1(1),* AA, Ethiopia.

National Meteorological Agency (NMA) (2001). *Initial national communication of Ethiopia to the United Nations Framework Convention on Climate Change.*

National Planning Commission (NPC) (2016). *Growth and Transformation Plan (GTP) II*(2015/16-2019/20),volume 1. Addis Ababa: The Federal Democratic Republic of Ethiopia.

Nisrane, F., G. Berhane, S. Asrat, G. Getachew, A. S. Taffesse, and J. Hoddinott (2011). Sources of Inefficiency and Growth in Agricultural Output in Subsistence Agriculture: A Stochastic Frontier Analysis, ESSP II Working Paper 19. Addis Ababa: IFPRI.

O'Brien, K. L. and R.M. Leichenko (2008). Human Security, vulnerability, and sustainable adaptation, Background Paper commissioned for the HDR 2007/2008: Fighting Climate Change: Human Solidarity in a Divided World. UNDP, NY.

Ramsey, J. B. (1969). Tests for specification error in classical linear least squares regression analysis.*Journal of the Royal Statistical Society*, B31: 250-71.

Schlenker, W., W.M. Hanemann, and A.C. Fisher (2006). The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *Review of Economics and Statistics,* 88(1): 113-25.

Shankar, B. and C. Thirtle(2005). Pesticide productivity and transgenic cotton technology: The South African smallholder case. *Journal of Agricultural Economics*, *56*(1): 97-116.

Tchale, H. and J. Suaer (2007). The Efficiency of Maize Farming in Malawi: A Bootstrapped Translog Frontier, *Cahiers d'economie et sociologie rurales*, 82-83.

The World Bank (2003). *Risk and Vulnerability Assessment, Draft Report for Ethiopia.* Washington, DC: The World Bank.

The World Bank (2006). *Managing water resources to maximize sustainable growth: a country water resources assistance strategy for Ethiopia.* Washington, DC: The World Bank.

UN-OHRLLS (2009). *The impact of climate change on the development project of the least developed countries and Small Island developing states.*

Wooldridge, J.M. (2002). *Econometric analysis of cross-section and panel data*. Cambridge, Massachusetts: The MIT Press.

Wu, D. (1973). Alternative Tests of Independence between Stochastic Regressors and Disturbances. *Econometrica,* 41: 733-50.

Yohannes H. (2016). A Review on Relationship between Climate Change and Agriculture. *Journal of Earth Science & Climatic Change,* 7:335.

CHAPTER FOUR

Farm-Heterogeneity and Persistent and Transient Productive Efficiencies in Ethiopia's Smallholder Cereal Farming

Abstract

This essay investigates persistent and transient productive efficiencies of Ethiopian cereal farmers for the period 1999-2015. It uses a 4-randomerror component stochastic frontier panel data model to distinguish between time-invariant farm heterogeneity and persistent and transient inefficiency. It compares this model with three other stochastic frontier panel data models in which one of the four components is missing. The models allow the estimation of persistent and transient efficiencies for each farmer and each time period. The first-order estimates of the parameters indicate that agro-chemicals, livestock, machinery and labor significantly enhanced cereal production. The results of the efficiency estimation indicate that the mean and dispersion of efficiencies among farmers differed by the model's specifications and the farmers' agro-ecological zones and sub-zones. The results also show that cereal farming was technically regressed at an increasing rate and exhibited increasing returns to scale. The results confirm that farmers in the study area were considerably inefficient in their cereal production, indicating that there was a lot of room for improvement using the present state of technology. The results further show that cereal growing farmers experienced much more transient inefficiency problems as compared to persistent inefficiencies. These findings are important and can be used to initiate agricultural policy options which are tailored to enhancing improvements in farming efficiency. The study recommends putting in place policies that improve measures that can reduce inefficiencies and improve the supply of agricultural inputs and also policies that can meet farmers' needs and which suit their agro-ecological zones.

Keywords: Stochastic frontier, unobserved heterogeneity, persistent efficiency, transient efficiency, cereal farming, agro-ecological zones, panel data, Ethiopia.

JEL Classification: C23, D21, D23, D24, O13, Q12.

1. Introduction

Studying the sources of growth in agricultural production and analyzing farm performance is an important step in assessing the developmental role that agriculture plays in developing countries. Knowing the efficiency levels of smallholder farmers has important implications for choosing development strategies, particularly in sub-Saharan Africa (SSA) where most countries derive over 60 per cent of their livelihoods from agriculture and related economic activities (Maurice et al., 2014). Ethiopia's economy is mainly based on agriculture as the sector contributes the largest share to the national GDP (averaged at 38.5 per cent), provides employment and livelihood to more than 83 per cent of the population and contributes 81 per cent to the country's total export earnings (AfDB, 2016).However, the sector is characterized by rain-fed agriculture, frequent droughts, high population pressure and severe land degradation; it is also vulnerable to climate change. The sector also has one of the lowest productivity levels in the world and is dominated by subsistence smallholders who usually cultivate areas which on average are less than 1.5 hectares (FAO, 2016).

Cereals are the most vital crop in Ethiopia comprising about two-third of the agricultural share of GDP and close to one-third of the national GDP (CSA, 2014). Cereals have a lion's share in the country's crop farming in terms of production volumes, farmland and farm households. According to CSA (2014) cereals comprised about 79 per cent of the total cropped area, 85 per cent of the grain crop production and engaged 81 per cent of the private farmers for the Meher season in the 2013/14 production year. As per CSA's yearly reports, cereal production had remarkable growth in Ethiopian crop farming during 2004-14. These publications indicate that cereal production consistently grew from an average of 16 million metric tons (MMT) in 2004-08 to 21.6 MMT during 2009-14. This shows an average of 18.8 MMTs growth at a rate of 2.74 per cent per annum for the decade 2004 to 2014.

However, despite the widely held view that agriculture plays a central role in Ethiopia's economic transformation, some researchers maintain that the sector did not perform as per expectations. According to Kassahun (2011) the sector was characterized with inefficiencies and poor productivity and cereal production showed a steady low-growth rate in the last two decades. These observations underline the importance of knowing the performance/efficiency levels of cereal farmers in Ethiopia. This information will help enhance food security which is an important issue for policymakers in agrarian countries like Ethiopia. Since the pioneering work of Farrell (1957) various studies have examined efficiency in crop farming in different countries using different methodologies. Most of these studies are based on Farrell-type measures of efficiency.

However, over the years various other methods of estimating production frontiers have also been developed and have come up with reliable efficiency measures. These frontier methods vary from econometric (a stochastic frontier analysis-SFA) to non-econometric (data envelopment analysis-DEA) methods. The stochastic production frontier (SPF) model introduced by Aigner et al., (1977) accommodates different circumstances (Battese and Coelli, 1992, 1995; Jondrow et al., 1982; Kumbhakar, 1991; Pitt and Lee, 1981; Schmidt and Sickles, 1984). SPF has been extensively used for estimating technical efficiencies. The SPF model is a better fit for an analysis of agricultural efficiencies because of the higher noise as a result of the stochastic nature of the production process and yield variability usually experienced in agricultural data.

Efficiency results from all such models are sensitive to the way in which they are modeled and interpreted and to the assumptions underlying the model mainly when panel data is used (Kumbhakar et al., 2014, 2015).The main reason for the different assumptions is that when panel data is available, the productive efficiency of a farm is composed of persistent and transient components of efficiency that cannot be captured distinctively by the earlier SPF models. In addition, these models do not treat explicitly unobservable individual effects from time-invariant inefficiency thus generating a miss-specification bias. Further, the effects of these factors may be captured by the term 'inefficiency' thereby producing biased inefficiency results. Hence, it is essential to control for heterogeneity and distinguish between transient and persistent components of inefficiency to estimate efficiency accurately. The econometric opportunity to include a remedy for these arguments has emerged recently. Colombi et al., (2014) and Kumbhakar et al., (2014) developed panel data models that separate short and long-term inefficiencies while controlling for heterogeneity by splitting the time-invariant component into unobservable farm-heterogeneity and long-term (persistent) inefficiency.

Several empirical works investigate the efficiency of Ethiopia's crop farming using different methodologies. However, thus far there have only been limited attempts at studying farming efficiency applying panel data SFP models. Most of the studies use simpler model specifications of the type used by Battese and Coelli (1992, 1995). These models have inherited the problems raised earlier. Moreover, to the best of my knowledge, only a few studies have tried to provide estimates of the two inefficiency components and they do not separate heterogeneities from inefficiencies. However, estimates of persistent inefficiencies provide useful information about farmers because high persistent inefficiency scores are indicators of non-competitiveness. This inefficiency may be due to the presence of structural problems in the organization of a farm's production process or the presence of systematic shortfalls in managerial capabilities or farmers' lasting habits of wasting inputs. The transient part of inefficiency on the other hand may stem from temporal behavioral aspects of the management, for example, from a non-optimal use of some inputs due to the presence of non-systematic management problems that can be solved in the short term. Further, as discussed by Kumbhakar et al., (2015)knowing estimates and information about the two components of inefficiency, especially in long panels and their separation from heterogeneity effects, is important as this allows farmers to use their resource/cost saving potential both in the short run and in the long run. Each component provides different information with different policy implications for promoting efficiency in the production of scarce resources.

Accordingly, this essay applies a recently proposed 4-component random error panel data SPF model following Kumbhakar et al., (2014) to estimate persistent and transient inefficiency by disentangling them from unobserved farm-heterogeneity effects for smallholder cereal farmers in Ethiopia using a partially balanced panel dataset. It also compares the results of this model with the other three SPF models in which one of the four components is missing. This study contributes to existing literature as it provides one of the first empirical analyses to show the presence of persistent and transient inefficiency using a novel econometric approach -- a 4-component random-error panel data SPF model -- for Ethiopia's smallholder cereal farmers. Second, to the best of my knowledge, this is the first panel data analysis which addresses the problems of individual and farm heterogeneities in measuring production efficiencies in Ethiopia's crop farming that disentangles farm heterogeneity from inefficiency effects. Thus, it provides valuable information on persistent and transient inefficiency and farm heterogeneity effects. Third, its analysis is based on agro-ecological zones (AEZs) which consider cereal farming at the farm-household level and thus it also considers output. Therefore, it is replicable elsewhere in the country, between regions and within AEZs.

The rest of the essay is organized as follows. Section 2 presents the method and data used; it also gives the specifications of the panel data stochastic frontier models, the estimation procedure and the dataset used in the analysis. Section 3 gives estimations and results and discusses the empirical findings. Section 4 gives a summary, conclusion and policy recommendations.

2. Method and Materials of the Study

2.1. A Partial Review of Panel Data Stochastic Frontier Models

Since their inception SPF models have been used for measuring and comparing the performance of individual production units within a geographic location, an industry or in the agricultural sector. Extensive research in this field has resulted in the rapid development of econometric techniques concerning specifications, estimations and testing issues of the models. These techniques have developed rapidly and have been implemented in many areas mostly using cross-sectional and panel data. The use of a panel data model in estimating producers' efficiencies helps avoid some of the problems related to distributional assumptions encountered in a cross-sectional approach. According to Schmidt and Sickles (1984) when inefficiency is time-invariant, panel data enables one to estimate inefficiency consistently without distributional assumptions. Panels also have the advantage of separating individual and time-specific effects from the combined effect (Heshmati et al., 1995). Further, panel data enables one to control individual heterogeneity effects, it has greater variability, less collinearity between variables, a higher degree of freedom and more efficiency; panel data is also more capable of identifying and measuring the effects that are not detected in cross-sectional or time-series data.

A panel data SPF model that was introduced in the early 1980s assumed inefficiencies to be individual-specific and time-invariant. That is, inefficiency levels may be different for different producers but they did not change over time. This means that an inefficient producer does not learn how to improve his performance over time. This might be the case in some situations where, for example, the soil quality is poor and a farm lacks water sources for irrigation, or inefficiencies are associated with managerial abilities and there is no change in the management and production technology for a farm during the study period (Kumbhakar et al., 2014, 2015). However, this seems unrealistic particularly when production competition is considered.

Another drawback of this approach is that farm heterogeneity cannot be distinguished from inefficiencies; all time-invariant heterogeneity is confounded by inefficiencies. This raises key questions on whether inefficiency has been persistent overtime or does it exist in time-varying units? And whether time-invariant individual effects represent persistent inefficiency or the effects are independent of the inefficiencies and capture persistent farm heterogeneity. Related to these questions and as discussed in Colombi et al., (2014) and Kumbhakar et al., (2014, 2015), several panel data SPF models have been developed to include both time-invariant and time-varying inefficiency effects. Some of these models were developed based on the assumption that all the time-invariant (fixed or random) effects were persistent inefficiencies (for example, Pitt and Lee, 1981; Schmidt and Sickles, 1984). Others were developed based on the assumption that the time-variant effects were transient inefficiencies without considering farm effects (for example, Battese and Coelli, 1992; Lee and Schmidt, 1993) and some others separated farm effects from transient inefficiencies without considering the possibility of persistent inefficiencies (for example, Greene, 2005a, 2005b).The models proposed by Kumbhakar (1991) and Kumbhakar and Heshmati (1995) are in between. These models treat farm effects as persistent inefficiencies and include another component to capture transient inefficiencies.

Some recently developed panel models provide information on whether a farm is characterized by the presence of both types of inefficiencies and are concerned with the separation of inefficiencies from heterogeneity effects (Colombi et al., 2014; Filippini and Greene, 2016; Kumbhakar et al., 2014; Tsionas and Kumbhakar, 2014) that may overcome some of the limitations of the earlier approaches. These recently developed models have been proposed with an error structure that is decomposed into four elements thus making it possible to account for the usual noise in the data, farmer/farm unobserved time-invariant heterogeneity and transient/short-term and persistent/long-term inefficiency components separately. They interpret transient inefficiency as short-term production inefficiency associated with changes in managerial skills or disruptions resulting from the adoption of new technologies. By contrast, persistent inefficiencies are long-term production inefficiencies due to structural or institutional factors which evolve slowly overtime. While long-run inefficiencies and farmer/farm unobserved-heterogeneity are both time-invariant effects, a major difference between them is that the latter is always beyond the control of the farmers (for example, geological/locational make-up of a farmer/farm and other physical features). Hence, having estimates and information about persistent and transient components of inefficiency and separating them from heterogeneity effects are important. Each component provides different information and has different policy implications.

In line with Heshmatiet al., (2017) and Rashidghalam et al., (2016) this essay uses four alternative SPF panel data models for estimating and analyzing persistent and transient efficiencies disentangling them from time-invariant farm effects. The first model is the basic version of panel data models: Schmidt and Sickles' (1984) fixed-effects model which assumes inefficiency effects to be time-invariant and individual specific. It thus offers estimates of persistent/long-run inefficiencies. The second model is a true fixed-effects panel data model proposed by Greene (2005a). This separates transient/short-run inefficiencies from persistent individual effects. The third model is a 3-component random error panel data model (Kumbhakar and Heshmati, 1995) that gives estimates of persistent and transient inefficiencies without accounting for farm heterogeneity. The fourth model is Kumbhakar et al.'s (2014) recently developed 4-component error panel data model that provides estimates of persistent and transient inefficiencies separating them from time-invariant farm effects and noise. Many other related studies (see Filippini and Greene, 2016; Heshmati et al., 2017; Kumbhakar et al., 2014; Poudineh, 2016; Rashidghalam et al., 2016; Tsionas and Kumbhakar, 2014) have compared efficiency estimates using alternative models estimating them either from random or fixed-effects models including the Schmidt and Sickles (1984) model.

2.2 Model Specifications and Estimation Procedure

Consider the traditional panel data SPF model:

$$\begin{aligned} (1) \qquad y_{it} &= \alpha_0 + x'_{it}\beta + \varepsilon_{it} - \tau_{it} \\ &= \alpha_0 + x'_{it}\beta + \varphi_{it} \end{aligned}$$

where, $i = 1,2,...,N$ is an index for farmer i and $t = 1, 2,...,T$, represent time. The variable y_{it} represents a farmer's output; x_{it} is a farmer's row vector of input variables plus other exogenous/control variables such as time trend(and depending on the specification of the production technology, squares of the inputs and their cross-product terms). The parameter α_0 is a common intercept; β is a vector of unknown parameters to be estimated; ε_{it} *and* τ_{it} are the idiosyncratic and inefficiency components of the 'composed error term', φ_{it};and $\tau_{it} \geq 0$ is a transient inefficiency term of individual *i* which is assumed to be *identically independently distributed (i.i.d.)*as half normal, that is, $\tau_{it} = |\mathrm{T}_{it}|$, *where* $\mathrm{T}_{it} \sim i.i.d.\ N^{+}(0, \sigma_{\mathrm{T}}^{2})$ .Similarly, ε_{it} is a random noise assumed to be $\varepsilon_{it} \sim i.i.d.\ N(0, \sigma_{\varepsilon}^{2})$.

2.2.1 Model Specification

This section gives the specifications of the four SPF panel data models used in this study. The specifications of all the models are based on the formulation of the model given in Equation 1.

Karagiannis and Tzouvelekas (2009); Kumbhakar et al., (2014) and Rashidghalam et al., (2016) provide a comparison of alternative specifications of inefficiency based on the same data. This essay focuses on four main models.

Model 1: Individual Effects Treated as Long-Run Inefficiencies

To specify a model with time-invariant inefficiency effects we treat the term τ_{it} in Equation1 as a time-invariant term u_i to represent long-run inefficiency to obtain:

$$(2) \qquad y_{it} = \alpha_0 + f(x_{it};\beta) + \varepsilon_{it} - u_i \quad ; \qquad u_i \geq 0$$

This model can be estimated assuming that either the inefficiency component (u_i) is a fixed parameter that influences the dependent variable directly (the fixed-effects model labeled the FE model) or assuming the inefficiency component (u_i) is a random variable that has a correlation with the independent variables (the random-effects model, labeled the RE model).This model has been criticized for its assumption about inefficiency as time-invariant inefficiency seems to be unrealistic, especially for a long panel dataset because this inefficiency term may capture some time-invariant farm attributes such as individual instinctive abilities and other persistent farm heterogeneities that are unrelated to the production process but which affect the output. Thus, these factors may be confounded with inefficiency and the model is miss-specified and tends to over-estimate inefficiency levels.

Model 2: Individual Effects Treated as Heterogeneity

To overcome the drawbacks of the FE model, Greene (2005a) proposed an extension of this model called the 'true' fixed-effects (TFE) model. The purpose of this model is to treat time-invariant farm heterogeneity and transient inefficiency effects separately. Hence, treating the inefficiency term τ_{it} as a time-varying term in Equation 1 but splitting the error term as: $\varepsilon_{it} = \mu_i + \upsilon_{it}$ we obtain:

$$(3) \qquad y_{it} = \alpha_0 + f(x_{it};\beta) + \mu_i + v_{it} - \tau_{it}$$

where, μ_i is random-effects to capture anytime-invariant farm heterogeneity, not inefficiency; τ_{it} represents transient inefficiency and v_{it} is a random shock with the following distribution:

$$(4) \qquad \tau_{it} \sim N^{+}(0,\sigma_{\tau}{}^{2}),\ v_{it} \sim N(0,\sigma_{v}{}^{2}), \mathit{and}\ \mu_i \sim N^{+}(0,\sigma_{\mu}^{2})$$

In this model if we treat μ_i as a fixed parameter that does not capture inefficiency then the model becomes a true fixed-effects model (TFE model).

The TFE model allows inefficiency to be time-variant and controls for farm heterogeneity for it to be captured by a farm specific intercept. However, the model views individual effects as different from inefficiency and assumes that inefficiency terms are always transient. Thus, it fails to capture persistent inefficiencies. Therefore, the individual effects cannot be distinguished from transient inefficiencies and the persistent component of inefficiency is completely absorbed in a farm's constant term. Hence, all time-invariant effects that are not necessarily inefficient are included as inefficiencies and therefore $\hat{\tau}_{it}$ might be picking up farm heterogeneity in addition to or even instead of inefficiencies (Kumbhakar and Heshmati, 1995).Consequently, this model is miss-specified and tends to underestimate transient inefficiency levels and can hence over-estimate efficiency scores.

Model 3: Individual Effects Treated as Persistent Inefficiencies

To overcome the downward bias inefficiency estimation of the TFE model and its ignorance about the persistent inefficiency component, Kumbhakar and Heshmati (1995) proposed a model that treats individual effects as persistent inefficiencies decomposing inefficiencies into persistent and transient components.

To formalize this model, we split the inefficiency term, τ_{it} in Equation 1 as: $\tau_{it} = \eta_i + u_{it}$ to obtain:

$$
\begin{aligned}
(5) \qquad & y_{it} = \alpha_0 + f(x_{it};\beta) + \varphi_{it} \\
& \varphi_{it} = \varepsilon_{it} - \tau_{it} \quad ; \quad \tau_{it} = \eta_i + u_{it} \quad \textit{so that} \\
& y_{it} = \alpha_0 + f(x_{it};\beta) + \varepsilon_{it} - \eta_i - u_{it}
\end{aligned}
$$

This model (KH model) splits the error term into three components where ε_{it} captures a random shock; $\eta_i \geq 0$ captures individual effects as persistent inefficiency; and $u_{it} \geq 0$ captures the transient inefficiency component. Unlike the TFE model, the KH model does not consider any time-invariant farm effects and hence confounds these effects in an individual's persistent inefficiencies. Consequently, the model is again mis-specified and is likely to produce persistent inefficiency estimates with an upward bias.

Model 4: Separation of Individual Heterogeneity from Persistent Inefficiencies

To overcome the limitations of these three models, Colombi et al., (2014), Kumbhakar et al., (2014) and Tsionas and Kumbhakar (2014) proposed a model that split the error term into four components-- persistent inefficiencies, transient inefficiencies, random farm effects and noise. Hence, we specify a model that distinguishes between persistent and transient inefficiencies and time-invariant inefficiencies from farm effects (Kumbhakar et al., 2014) using the decompositions $\tau_{it} = \eta_i + u_{it}$ *and* $\varepsilon_{it} = \mu_i + \upsilon_{it}$ in Equation 1 to obtain:

$$
(6) \qquad y_{it} = \alpha_0 + f(x_{it};\beta) + \mu_i + \nu_{it} - \eta_i - u_{it}
$$

This model (the KLH model) decomposes the error term, φ_{it} into four components as: $\varphi_{it} = \mu_i + \nu_{it} - \eta_i - u_{it}$; where μ_i is a random farm effect that captures time-invariant farm's heterogeneity (for example, oil quality) which has to be disentangled from persistent individual effects (for example, a farmer's skills); υ_{it} is the idiosyncratic random component; $\eta_i \geq 0$ captures persistent inefficiencies; and $u_{it} \geq 0$ captures transient inefficiency effects. Without μ_i Equation 6 is reduced to the KH model and without η_i it is the same as the TFE model.

2.2.2 Model Estimation Procedures

To estimate the FE model we reformulated Equation 2 to obtain the following estimable model:

$$\begin{aligned} y_{it} &= \alpha_0 + f(x_{it};\beta) + \varepsilon_{it} - u_i = (\alpha_0 - u_i) + f(x_{it};\beta) + \varepsilon_{it} \\ &= \alpha_i + f(x_{it};\beta) + \varepsilon_{it} \end{aligned} \tag{7}$$

Equation 7 is like a standard fixed-effects panel data model (Schmidt and Sickles, 1984), where $\alpha_i = \alpha_0 - u_i$ is farm-specific intercepts. Here u_i *and* α_i are individual effects and are assumed to be fixed-parameters to be estimated along with the parameter vector β. One can apply the standard fixed-effects panel data estimation method to obtain $\hat{\alpha}_i$ and the following transformation to obtain an estimate for u_i :

$$\hat{u}_i = \max_i(\hat{\alpha}_i) - \hat{\alpha}_i \geq 0, \qquad i = 1,\dots,N \tag{8}$$

and obtain farm specific technical efficiency estimate $TE_i = Exp(-\hat{u}_i)$.This formulation implicitly assumes that the most efficient unit in the sample is 100 per cent efficient so that inefficiencies for other farmers are relative to the best farmer.

We estimated the TFE model by making a distributional assumption on the random error. Different estimation methods have been proposed for estimating the KH and KLH models. Colombi et al., (2014) used the single stage maximum likelihood estimation (MLE) method based on the distributional assumptions of the4-error components; Kumbhakar and Heshmati (1995) and Kumbhakar et al., (2014) used a multi-step procedure; and Filippini and Greene (2016) used the simulated ML approach. However, due to its simplicity we used the multi-step estimation procedure suggested by Kumbhakar et al., (2014, 2015) for the KH and KLH models. The multi-step procedure has the advantage of avoiding strong distributional assumptions by estimating the model using the ML method. Similar studies (Kumbhakar et al., 2014; Poudineh, 2016; and Rashidghalam et al., 2016) have also applied the same estimation methods to compare efficiency estimates from several fixed-effects models including the Schmidt and Sickles (1984) model. In what follows we present the multi-step approach for the two models.

The KH model can be estimated in four steps. The steps are described in Kumbhakar et al., (2015).For this we rewrite the model in Equation 5 as:

$$\begin{aligned} & y_{it} = \alpha_i + f(x_{it};\beta) + \omega_{it}, \\ & \alpha_i = \alpha_0 - \eta_i - E(u_{it}) \ and \ \omega_{it} = \varepsilon_{it} - (u_{it} - E(u_{it})) \end{aligned} \tag{9}$$

In this case the error component ω_{it} has zero mean and constant variance. Thus, the model in Equation 9 which fits the standard panel data model with individual effects can be estimated either by the least squares dummy variable (LSDV)or by the generalized least squares method. Under the LSDV framework, the model can be estimated in four steps using a multi-step procedure as: In step 1, we estimate Equation 9 using the standard within fixed-effects panel data model to obtain consistent estimates of β. In step 2, we estimate persistent inefficiencies, in which we obtain their components $\hat{\eta}_i$ which can be used to estimate persistent technical efficiency $PTE = \exp(-\hat{\eta}_i)$. In step 3, using the standard half-normal SF model we estimate α_0 and the parameter associated with ε_{it} *and* u_{it}. Finally, in step 4, we use the JLMS technique to estimate the residual inefficiency u_{it}. This procedure predicts the residual inefficiency component $\hat{u}_{it}$ which can be used for estimating residual technical efficiency $RTE_{it} = \exp(-\hat{u}_{it})$. Finally, the overall technical efficiency (OTE) is obtained from the product of persistent and residual efficiencies, that is, $OTE_{it} = PTE_i \times RTE_{it}$

To estimate the KLH model, we reformulated Equation 6 as:

$$y_{it} = \alpha_0^* + f(x_{it};\beta) + \alpha_i + \omega_{it} \tag{10}$$

where, $\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it})$; *and* $\alpha_i = \mu_i - \eta_i - E(\eta_i)$; *and* $\varepsilon_{it} = \nu_{it} - u_{it} + E(u_{it})$

With this specification α_i *and* ω_{it} have zero mean and constant variance since Equation 10is a familiar panel data model. Like in the previous case we used the 3-step approach to estimate the KLH model. In the first step, we used the standard fixed-effect panel regression to estimate $\hat{\beta}$. This procedure also gives predicted values of α_i *and* ε_{it}, denoted by $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}^*$. In step 2, we estimated the time-varying technical efficiency using the predicted value of ε_{it}^* from the previous step using the standard stochastic frontier technique. This procedure predicts the time-varying residual technical inefficiency which can be used to estimate $RTE_{it} = \exp(-u_{it} | \varepsilon_{it}^*)$. In step 3 we estimated η_i, following a procedure similar to the one in step 2. For this we used the standard pooled half-normal stochastic frontier model to obtain estimates of the persistent inefficiency component η_i. Then PTE can be estimated using the formulae $PTE_i = \exp(-\hat{\eta}_i)$ and $OTE_{it} = PTE_i \times RTE_{it}$. Summary statistics of the main characteristics of the four models applied are given in Table 4.1.

Table 4.1 Summary of the Main Characteristics of the Four Models Applied

Models	*Model 1*	*Model 2*	*Model 3*	*Model 4*
Full composed error term $\varphi_{it} = \varepsilon_{it} - \tau_{it}$	$\varphi_{it} = \varepsilon_{it} - u_i$ $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ $u_i \sim N^+(0, \sigma_u^2)$	$\varphi_{it} = \mu_i + v_{it} - \tau_{it}$ $\tau_{it} \sim N^+(0, \sigma_\tau^2)$, $v_{it} \sim N(0, \sigma_v^2)$, $and\ \mu_i \sim N(0, \sigma_\mu^2)$	$\varphi_{it} = \varepsilon_{it} - \eta_i - u_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$, $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$, $and\ \eta_i \sim N^+(0, \sigma_\eta^2)$	$\varphi_{it} = \mu_i + v_{it} - \eta_i - u_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$, $v_{it} \sim N(0, \sigma_v^2)$, $\mu_i \sim N(0, \sigma_\mu^2)\ and$ $\eta_i \sim N^+(0, \sigma_\eta^2)$
Specifications	Persistent inefficiency	Heterogeneity	Persistent & transient inefficiency	Heterogeneity, persistent & transient inefficiency
Persistent inefficiency estimator	$E(u_i \| \varphi_{it})$	None	$E(\eta_i \| \varphi_{it})$	$E(\eta_i \| \varphi_{it})$
Transient inefficiency estimator	None	$E(\tau_{it} \| \varphi_{it})$	$E(\tau_{it} \| \varphi_{it})$	$E(\tau_{it} \| \varphi_{it})$
Estimation Method	COLS	ML	ML	ML

Note: Model 1is the fixed-effects model, Model 2 is the true fixed-effects model, Model 3is the Kumbhakar and Heshmati (1995)model, Model 4 is the Kumbhakar, Lien and Hardaker (2014) model; corrected ordinary least squares (COLS); ML-Maximum Likelihood.

2.3 The Empirical Model

The production function $f(x_{it}; \beta)$ in (Equations1 to 4) is specified using a translog (TL) functional form because of its flexibility (Christensen et al., 1973). Hence, assuming a TL with the time-trend representation we estimated a stochastic frontier panel data model using the following specification:

$$\ln y_{it} = \alpha_0 + \sum_{j=1}^{J} \beta_j \ln X_{jit} + \beta_t T_t + \frac{1}{2}\left(\sum_{j=1}^{J} \sum_{k=1}^{J} \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} T_t^2 \right) + \sum_{j=1}^{J} \beta_{jt} \ln X_{jit} T_t + \varepsilon_{it} - \tau_{it} \tag{11}$$

where, $\ln y_{it}$ is the natural logarithm of output measure of farmer*;* $i = 1,2,...,N$; in time period *t*, $t = 1,2,...,T$*;* and $\ln X_{it}$ is a vector of natural logarithm of *j*, $j = 1,2,...,J$ inputs. The explanatory variable T is a time trend and is a proxy for the exogenous rate of technical change, while all other variables ($\alpha, \beta, \varepsilon\ and\ \tau$) maintain their previous definitions as in Equation 1.

Elasticities (E), technical changes (TC) and returns to scale (RTS)

Since the coefficients of the TL production function do not have direct interpretations, we computed elasticities of output with respect to each input. As all the variables are expressed in their logarithms their elasticities can be obtained from a partial differentiation of the production function with respect to appropriate inputs based on:

(12) $$E_{jit} = \frac{\partial \ln y_{it}}{\partial \ln X_{jit}} = \beta_j + \beta_{jj} \ln X_{jit} + \beta_{jt} T_t \quad ,$$

the rate of TC and RTS is obtained from:

(13) $$TC_{it} = \frac{\partial \ln y_{it}}{\partial \ln T_t} = \beta_t + \beta_{tt} T_t + \sum_{j=1}^{J} \beta_{jt} \ln X_{jit} \;\; and \; RTS_{it} = \sum_{j=1}^{J} E_{jit} \; .$$

Elasticity measures the responsiveness of output to a 1 per cent change in the j^{th} input used by farmer i at time t. Note that the exogenous technical change (TC) can be further decomposed into the pure $(\beta_t + \beta_{tt} T)$ and non-neutral ($\sum_{j=1}^{J} \beta_{jt} \ln X_{jit}$) components. Pure TC refers to a neutral shift of the production function due to time alone, non-neutral TC means input-biased TC. RTS measures the percentage change in output in response to a proportional 1 per cent increase in all inputs simultaneously. Technology exhibits; increasing, constant or decreasing RTS if RTS is greater than, equal to or less than one respectively. All input elasticities, RTS and TC are computed at every data point.

2.4. Data and Variables in the Study

This essay's data source is the Ethiopian Rural Household Survey (ERHS) dataset collected from randomly selected farm households in rural Ethiopia. It includes farm production and economic data collected at 5-year intervals from local farmers associations (FAs) that were selected to represent the country's diverse farming systems. Originally, the first four waves of the survey were conducted in collaboration with the Department of Economics, Addis Ababa University and the International Food Policy Research Institute (IFPRI).The last round was extended to form a sub-sample from the original respondents covering eight FAs following a similar strategy. This comprised of 503 farm households and was conducted by this researcher in 2015 with financial support from the Environment for Development (EfD) initiative at the University of Gothenburg, Sweden. Consequently, this essay employs data from four survey rounds (1999, 2004, 2009 and 2015) covering eight FAs thus forming a partially balanced panel of 446 households and 1,648 observations. These four rounds were selected to allow for even time spacing and covering approximately similar time frames.

We used aggregated cereal output value measured in Ethiopian birr (ETB) as a dependent variable while the explanatory variables are: labor employed measured in man-day units (MDUs); cereal sown farmlands in hectares; amount of fertilizers used in kilograms; agricultural machinery implements in ETB; agro-chemicals (including pesticides, herbicides and insecticides) applied in ETB; livestock ownership in tropical livestock units (TLUs) as a proxy for wealth and livestock asset endowments; and oxen used in numbers. The last two inputs are mainly used as animal power in traditional farming during land preparation and harvesting periods. We also used a time trend and its square. The time trend captures the shift in production over time representing technical changes, while the squared trend captures the non-linear shift in the production function over time. All monetarily measured variables were transformed to fixed ETB prices. The input variable 'seeds' was excluded from the analysis due to lack of information.

2.5 Descriptive Summary

Table 4.2 presents summary statistics of the data on the different variables used in the stochastic frontier. Farmers' real value of output captured in thousands of Ethiopian birr (ETB) was used as a dependent variable in the stochastic frontier models. As shown in the table, its mean was about 11,313 birr ranging from 83 to 444,810 birr for the study period. The mean of cereal output produced during the period was about 1,952kg ranging between 34kg and 51,100kg per farm during the study period. Evolution of cereal production over time reveals that production increased consistently across all survey years as the mean production increased from nearly 1,260kg in 1999 to nearly 3,020kg in the 2015 survey/production year.

Table 4.2 Summary Statistics of Input and Output Variables (NT = 1,648)

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Output produced(kg)	1,952.25	2,681.81	34.00	51,100.00
Output value (ETB)	11,313.74	23,082.90	83.00	444,810.00
Fertilizers used(kg)	116.10	138.85	0.08	1400.00
Agro-chemicals(ETB)	133.90	447.17	0.01	8560.00
Farm labor (MEU)	342.62	714.21	3.00	8333.88
Machinery(ETB)	336.69	1775.80	0.50	36540.00
Livestock units (TLUs)	6.49	5.93	0.00	58.80
Number of oxen used	1.77	1.33	0.01	9.00
Planted-area (Hec.)	1.75	1.28	0.02	11.00

Source: Author's computations.

The farmers cultivated cereals on average on about 1.8 hectares and used 342.6MDUs of labor. Fertilizer application was minimal with an average of 116.1kg per farm household while the expenses on agro-chemicals were on average 133.9ETB. The farmers spent 336.27ETB for agricultural machinery used per farm household. Average livestock ownership was 6.5TLUs and average oxen used was around 1.8 oxen meaning that farms on average used two oxen ranging from no ox to nine oxen per farm household. One fact which emerges from the descriptive statistics is that growth in the real value of output was partly due to increasing use of factors of production.

3. Empirical Results and Discussion

3.1 Parameter Estimates and Technical Change

Table 4.3 presents estimates of the translog production frontier parameters obtained from the econometric estimations of the alternative models. As shown in Table 4.3, similar estimates of the production parameters were obtained from the estimations of models 1, 3 and 4. Similar results were also obtained in related studies using the same dataset and applying similar models as model 1, 3 and 4 (see Kumbhakar et al., 2014; Poudineh, 2016; Rashidghalam et al., 2016). This is due to the models' assumptions and specifications. Most of the parameter estimates from the models were significantly different from zero at the 5 per cent level or lower. For all the models the estimated first-order parameters (β_i) had the anticipated (positive) sign and magnitude (between zero and one),whereas the bordered Hessian matrix of the first and second-order partial derivatives was negative and semi-definite indicating that all regularity conditions of the production economic theory which require that the partial output elasticities be non-negative and less than one(that is, positive and diminishing marginal products) were valid at the point of approximation. Thus, the results of all the four models behaved well in production frontier functions. The estimates of the first-order parameters with respect to agro-chemicals, labor, machinery, oxen and livestock were all statistically significant. This suggests that cereal production in the study area was the most responsive to these inputs. Hence, an increase in agro-chemicals, machinery, labor use and more livestock units that may include plowing oxen enhanced cereal production.

Estimates of the time-trend and its squared term were significantly positive at the 1 per cent level showing that cereal farmers experienced technical changes (TC) at an increasing rate over the sample period. Estimates of time interacted with farmland area were positive implying that TC was land using. The coefficients of time interactions with other inputs were negative and significant implying factors using TC for these inputs and suggesting input saving TC. Estimates of time interactions with agro-chemicals were not significant implying technical neutrality with respect to this input. However, the overall TC was not neutral because some production factors significantly changed over time.

Output Elasticities and Returns to Scale

Average estimates of production input elasticities estimated at the mean of the data computed from Equation 12, returns to scale and technical changes are presented in Table 4.4. Estimates of production elasticities with respect to all inputs evaluated at the mean of the data were significantly different from zero. All point elasticity estimates across models were positive, indicating positive marginal products of inputs. The positive signs of the elasticities further indicate that lack of these inputs hampered agricultural activities and hence output levels. Estimates of production elasticities indicate that each input contributed significantly to cereal production, however, the magnitude of the elasticities differed across models. For instance, if a farmer increased the number of the oxen by 1 per cent, keeping other inputs constant, this increased cereal production by 0.450 per cent (FE, KH and KLH models) and 0.465 per cent (TFE model). Similarly, an increase in livestock rearing by1 per cent increased production by 0.274 per cent in the TFE model and by 0.240 per cent in the other models. An increase in agro-chemicals by 1 per cent increased production by 0.064 per cent for the TFE model and 0.068 per cent in the other models and increasing cultivated land area by 1 per cent increased production by 0.276 per cent in the TFE model and by 0.333 per cent in the other models.

Table 4.3 Parameters estimate form the TL production frontier across models (NT = 1,648)

		Model 1		***Model 2***		***Model 3 & 4***	
Variables		***Estimate***	***Std. Err.***	***Estimate***	***Std. Err.***	***Estimate***	***Std. Err.***
Fertilizer	β_{x1}	0.063	0.080	0.089	0.067	0.063	0.080
Agro-chemicals	β_{x2}	0.108*	0.059	0.098**	0.050	0.108*	0.059
Labor	β_{x3}	0.350***	0.114	0.341***	0.095	0.350***	0.114
Machinery	β_{x4}	0.289***	0.077	0.287***	0.064	0.289***	0.077
Livestock	β_{x5}	0.194	0.126	0.223**	0.106	0.194	0.126
Oxen	β_{x6}	0.382	0.292	0.391*	0.244	0.382	0.292
Area	β_{x7}	0.069	0.133	0.014	0.112	0.069	0.133
Fertilizer*Fertilizer	β_{x11}	-0.002	0.018	0.003	0.015	-0.002	0.018
Agrochemicals square	β_{x22}	-0.005	0.014	-0.002	0.012	-0.005	0.014
Labor*Labor	β_{x33}	0.035	0.023	0.030	0.019	0.035	0.023
Machinery*Machinery	β_{x44}	0.058***	0.016	0.061***	0.013	0.058***	0.016
Livestock*Livestock	β_{x55}	0.121***	0.028	0.125	0.024	0.121***	0.028
Oxen*Oxen	β_{x66}	-0.224	0.223	-0.214	0.186	-0.224	0.223
Area*Area	β_{x77}	-0.118***	0.026	-0.125***	0.022	-0.118***	0.026
Fertilizer*Agro-chemicals	β_{x12}	-0.004	0.013	-0.008	0.011	-0.004	0.013
Fertilizer*Labor	β_{x13}	0.019	0.025	0.013	0.021	0.019	0.025
Fertilizer*Machinery	β_{x14}	-0.002	0.015	-0.003	0.012	-0.002	0.015
Fertilizer*Livestock	β_{x15}	-0.093***	0.029	-0.099***	0.025	-0.093***	0.029
Fertilizer*Oxen	β_{x16}	0.102	0.066	0.111**	0.056	0.102	0.066
Fertilizer*Area	β_{x17}	0.111***	0.035	0.126***	0.029	0.111***	0.035
Agro-chemicals*Labor	β_{x23}	-0.012	0.02	-0.007	0.016	-0.012	0.02
Agro-chemicals*Machinery	β_{x24}	0.000	0.013	0.001	0.011	0.000	0.013
Agro-chemicals*Livestock	β_{x25}	0.068***	0.028	0.071***	0.024	0.068***	0.028
Agro-chemicals*Oxen	β_{x26}	-0.108**	0.054	-0.110**	0.045	-0.108**	0.054
Agro-chemicals*Area	β_{x27}	-0.007	0.028	-0.002	0.023	-0.007	0.028
Labor*Machinery	β_{x34}	0.068***	0.019	0.070***	0.016	0.068***	0.019
Labor*Livestock	β_{x35}	0.051	0.046	0.045	0.038	0.051	0.046
Labor*Oxen	β_{x36}	-0.103	0.096	-0.098	0.08	-0.103	0.096
Labor*Area	β_{x37}	-0.043	0.043	-0.036	0.036	-0.043	0.043
Machinery*Livestock	β_{x45}	-0.003	0.028	0.002	0.024	-0.003	0.028
Machinery*Oxen	β_{x46}	0.021	0.054	0.018	0.045	0.021	0.054
Machinery*Area	β_{x47}	-0.042	0.027	-0.042*	0.023	-0.042	0.027
Livestock*Oxen	β_{x56}	-0.190	0.129	-0.206**	0.108	-0.190	0.129

Livestock*Area	β_{x57}	-0.193***	0.07	-0.194***	0.058	-0.193***	0.07
Oxen*Area	β_{x67}	0.333***	0.144	0.329***	0.12	0.333***	0.144
Time*Fertilizers	β_{x1t}	-0.024*	0.014	-0.026**	0.012	-0.024*	0.014
Time*Agro-chemicals	β_{x2t}	-0.010	0.011	-0.011	0.009	-0.010	0.011
Time*Lobar	β_{x3t}	-0.115***	0.022	-0.119***	0.018	-0.115***	0.022
Time*Machinery	β_{x4t}	-0.029*	0.018	-0.037**	0.015	-0.029*	0.018
Time*Livestock	β_{x5t}	-0.049*	0.026	-0.051**	0.022	-0.049*	0.026
Time*Oxen	β_{x6t}	0.086*	0.052	0.073*	0.044	0.086*	0.052
Time*Area	β_{x7t}	0.114***	0.031	0.118***	0.026	0.114***	0.031
Time(1=1999,…,4=2015)	β_t	0.688***	0.163	0.666***	0.139	0.688***	0.163
Time*Time	β_{tt}	0.355***	0.052	0.394***	0.047	0.355***	0.052
Constant	β_0	4.683***	0.396	4.155***	0.457	4.683***	0.396
σ_u		0.512		5.503**	2.933	0.512	
σ_v		0.748		-0.954***	0.038	0.748	
Γ		0.319		0.385***	0.015	0.319	
R^2		0.758				0.758	
LogL				-1564.86		-1563.25	

Notes: *: p<0.05; **: p<0.01; ***: p<0.001.Model 1: the FE_Model; Model 2: the TFE_Model; Model 3: the KH_Model and Model 4: the KLH_Model.

Subscripts on β_x coefficients refer to inputs: 1 = Fertilizers; 2 = Agro-chemicals; 3 = Labor; 4 = Machinery; 5 = Livestock; 6 = Number of oxen; and 7 = Planted area.

Moreover, as can be observed from Table 4.3, in almost all the models for all productive inputs, the elasticities with respect to oxen were the highest, elasticities with respect to cultivated land size were the second highest and those for fertilizers were the least. These indicate that more oxen contributed the most to cereal production, followed by land. The least contribution was of fertilizers. The results suggest that traction animal power contributed to higher levels in cereal farming but this may be because animal traction power is a dominant form of land preparation under conventional farming. Our results are similar to what other studies have found in Ethiopia (Gebreegziabher et al., 2005).

Table 4.4 Mean Input Elasticities, Returns to Scale and Technical Changes across Models

Input	***Model 1***	***Model 2***	***Model 3 & 4***
Fertilizers	0.004	0.012	0.004
Agro-chemicals	0.068	0.064	0.068
Farm labor	0.224	0.191	0.224
Machinery	0.254	0.256	0.254
Livestock	0.240	0.274	0.240
Oxen	0.450	0.465	0.450
Planted-area	0.333	0.276	0.333
RTS	1.572	1.538	1.572
TC	0.876	0.902	0.876

Source: Author's computations.

We also calculated returns to scale (RTS) and technical changes (TC) computed from Equation 13 in all the four models and used the results for a robustness check. Accordingly, as can be seen from Table 4.4 estimates of RTS evaluated at the mean data point were similar across models; however, their magnitudes were model specific. Specifically, RTS was 1.538 in the TFE model and 1.572 in the other models.

Hence, in general our results suggest that cereal growing farmers in the sample exhibited increasing returns to scale in all the models. Our empirical results indicate that all models predicted similar patterns of technical change. All alternative estimators revealed positive TC estimates which are progressive at an increasing rate with the time pattern being model specific. In particular, TC estimates clearly indicate technical regress at an increasing rate of 0.901 in the TFE model and 0.880 in the other models. This is a result of an increase in farming skills, improved seed quality and skills in the use of machinery and fertilizers.

3.2. Technical Efficiency

Table 4.5 gives the distribution of persistent and transient efficiency scores obtained from alternative models. The FE model produced values of technical efficiency that are time-invariant and therefore should reflect persistent efficiencies. Results from the KH and KLH models provide persistent as well as transient technical efficiency components.

Table 4.5 Distribution of Persistent, Transient and Overall Technical Efficiencies

Percentile	Model 1, TE_PTE	Model 2, TFE_TTE	Model 3, KH_PTE	Model 3, KH_TTE	Model 3, KH_OTE	Model 4, KLH_PTE	Model 4, KLH_TTE	Model 4, KLH_OTE
1%	0.085	0.729	0.085	0.385	0.044	0.642	0.385	0.277
5%	0.123	0.780	0.123	0.515	0.076	0.700	0.515	0.396
10%	0.140	0.835	0.140	0.572	0.093	0.719	0.572	0.441
25%	0.185	0.928	0.185	0.641	0.127	0.756	0.641	0.500
50%	0.268	0.960	0.268	0.704	0.185	0.798	0.704	0.559
75%	0.388	0.984	0.388	0.751	0.269	0.831	0.751	0.600
90%	0.508	0.999	0.508	0.789	0.360	0.852	0.789	0.634
95%	0.614	1.000	0.614	0.809	0.411	0.864	0.809	0.650
99%	0.837	1.000	0.837	0.851	0.576	0.881	0.851	0.696
Mean	0.304	0.944	0.304	0.689	0.210	0.791	0.689	0.545
Std. Dev.	0.155	0.065	0.155	0.094	0.111	0.053	0.094	0.082
Min.	0.054	0.427	0.054	0.141	0.020	0.567	0.141	0.105
Max.	1.000	1.000	1.000	0.927	0.840	0.889	0.927	0.783
Yearly mean technical efficiency scores								
1999		0.964		0.695	0.213		0.695	0.550
2004		0.958		0.661	0.195		0.661	0.523
2009		0.941		0.707	0.215		0.707	0.559
2015		0.918		0.684	0.210		0.684	0.541

Source: Author’s computations.

The TFE model, which does not include persistent efficiencies, produced values that were time-variant and therefore reflect the overall (transient) efficiencies. In general, the results illustrate significant variations in efficiency estimations across models and that the efficiency scores are sensitive to the model's specifications. The estimated persistent technical efficiency in model 1 is the same as the estimated persistent technical efficiency in model 3, which is in line with results from the same model in Kumbhakar (2014) and Rashidghalam et al., (2016). Similarly, the estimated transient technical efficiency in model 3 is the same as the estimated transient technical efficiency in model 4 which is also in line with transient (or residual) technical efficiency estimates for KH and KLH models (Kumbhakar et al., 2014; and Poudineh, 2016; Rashidghalam et al., 2016).This is due to the model's assumptions and specifications.

3.2.1 Time-Invariant/Persistent Technical Efficiency

As shown in Table 4.5, mean persistent technical efficiencies in the FE and KH models were 0.30 with larger dispersions. On the other hand, mean persistent efficiency captured by the KLH model was 0.79 which is significantly higher than the mean of FE and KH models with much lower efficiency variations. Hence, after comparing efficiency estimates across models the results obtained by the FE and KH models do not provide precise information on the level of persistent efficiencies. The reason for this is that these models do not separate unobserved persistent farm-heterogeneity from inefficiencies and parts of time-invariant farm effects can be confounded in persistent inefficiencies. Thus, the models tend to over-estimate inefficiency scores, hence generating lower estimates of persistent efficiencies.

Distribution of persistent efficiencies further shows that almost 58 per cent of the farmers were operating below the mean score in the KH model as against 44 per cent in the KLH model. In the KLH model, 94 per cent of the farmers had persistent efficiency scores between 0.71 and 0.90. On the other hand, in the FE and KH estimates more farmers had efficiency scores between 0.21 and 0.30 implying that most cereal farmers in the study area faced severe persistent production inefficiency problems.

3.2.2 Time-Varying (Transient) Technical Efficiency

The mean transient technical efficiencies obtained from the KH, KLH and TFE models is 0.21, 0.55 and 0.94 respectively. The result shows that there were fewer farmers with transient efficiency scores below 90 per cent in the TFE model than there were in the other two models. The variations in transient efficiency estimates by these models are due to their underlying assumptions. The TFE model assumes that inefficiency is always time-varying and controls for unobserved farm heterogeneity to be constant over time without considering individual effects. However, if a farm household is characterized by persistent individual effects, this becomes part of farmer-specific constant terms. Consequently, the model underestimates transient inefficiency levels which results in intransient efficiency scores inflating upwards.

Unlike the TFE model, the KH model does not consider any time-invariant effects; it is associated with a farm and treats all time-invariant farm effects as inefficiencies. Hence, it confounds farm effects with individual persistent inefficiencies. Thus, the part of inefficiency persistence captured by this model is over-estimated. Consequently, the model is likely to produce over-estimated persistent inefficiency scores and therefore generate lower estimates of persistent efficiencies. But we know that OTE (which is time-variant) is a product of persistent and residual efficiencies. Thus, transient efficiencies in the KH model are lower due to low persistent efficiency estimates. These characteristics of the KH model, together with those of the TFE model, suggest that latent farm and individual effects as unobserved heterogeneities are significant in the sample and require us to reconsider our modeling to obtain more accurate efficiency estimates.

Thus, believing that the true measure of efficiency may be somewhere between these extremes we considered a recently developed more flexible efficiency model called the GTFEM or KLH model which might come closer to capturing true efficiency. This model overcomes some of the limitations of the earlier models by decomposing overall inefficiencies into persistent and residual components; it also distinguishes time-invariant farm effects from persistent inefficiencies. Like the KH model, the KLH model decomposes efficiencies into persistent and transient components. However, the separation of persistent inefficiencies from time-invariant farm effects results in higher estimates of persistent inefficiencies as compared to the estimates in the KH model with low variations. Thus, mean transient efficiency results in the KLH model are higher as compared to the KH model and less as compared to the TFE model. The frequency distribution of transient efficiencies also shows that 46 per cent of the farmers were operating below the mean score in the KLH model as opposed to 60 per cent in the KH model.

In general, the variability in efficiency scores across the models that we considered clearly demonstrates the existence of significant unobserved farm/individual heterogeneity in the sample and should be considered in efficiency modeling and specifications. This is in line with the findings of Heshmati et al., (2017) and Kumbhakar et al., (2014). Besides, the findings also show that efficiency estimates varied over time. Transient efficiencies varied across years; these decreased during the study period and 2009 was the most efficient year and 2015 was the least efficient year. The patterns of efficiency ratings through time show that, the level of transient efficiencies was quite low and was mostly concentrated between 0.11 and 0.20 in the KH model and it was quite moderate and concentrated between 0.51 and 0.60 in the KLH model in all the years.

Further, to get a better picture of the efficiency components in different models, we used density plots for them. These density plots show that the distribution of persistent efficiencies in the FE and KH models was identical (Figure 4.1) and except for some values in the upper tail, most of the farmers had low levels of efficiency in so far as their persistent efficiencies are concerned. This was, however, not the case in the KLH model as it provided the highest persistent efficiency scores, having a mean that was 50 per cent higher as compared to the FE and KH models with the least dispersion.

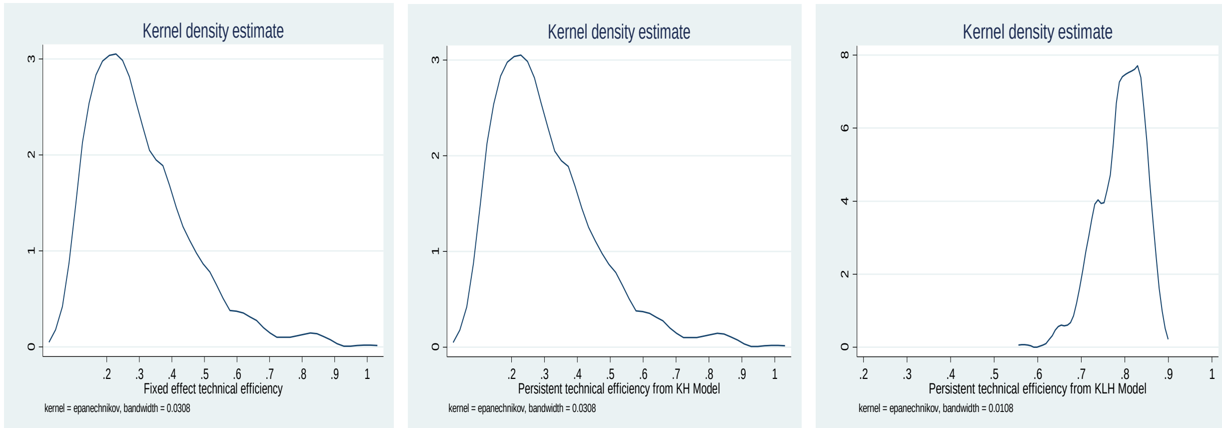


Figure 4.1 Distributions of Persistent Technical Efficiencies across Models

Regarding the distribution of transient efficiencies since the individual-effects are not considered to be inefficiencies in the TFE model this leads to high efficiency scores (Figure 4.2) with low dispersion (Figure 4.3) as compared to the other two models.

The distribution of transient efficiencies in the KH model is similar to its persistent component but its mean is pushed back by about 10 per cent. Whereas in the KLH model most of the farmers were found to have moderate levels of transient efficiency scores, lying between those in the TFE and KH models (Figure 4.2) the scores were spread in the TFE model (low spread) and the KH model (high spread) (lower part of Figure 4.3). Similar results were found by Heshmati et al., (2017) and Kumbhakar et al., (2014).

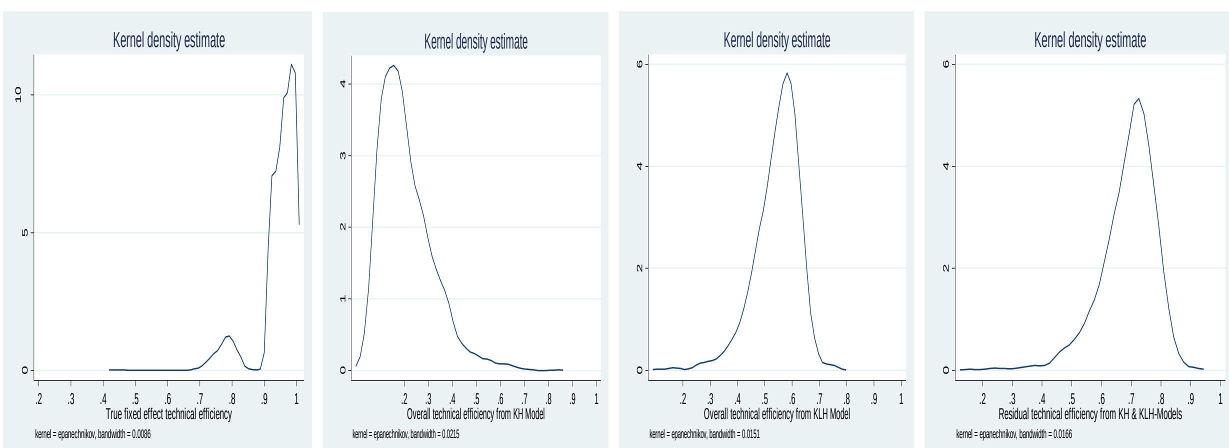


Figure 4.2 Distributions of Transient Technical Efficiencies across Models

The spread of the residual efficiency component in the KH and KLH models as a main element of overall efficiency was significantly higher for the persistent component as compared to the residual component in both the models (Figure 4.2). Thus, the results suggest that persistent inefficiencies were a bigger problem compared to residual/transient inefficiencies in the sampled cereal farmers.

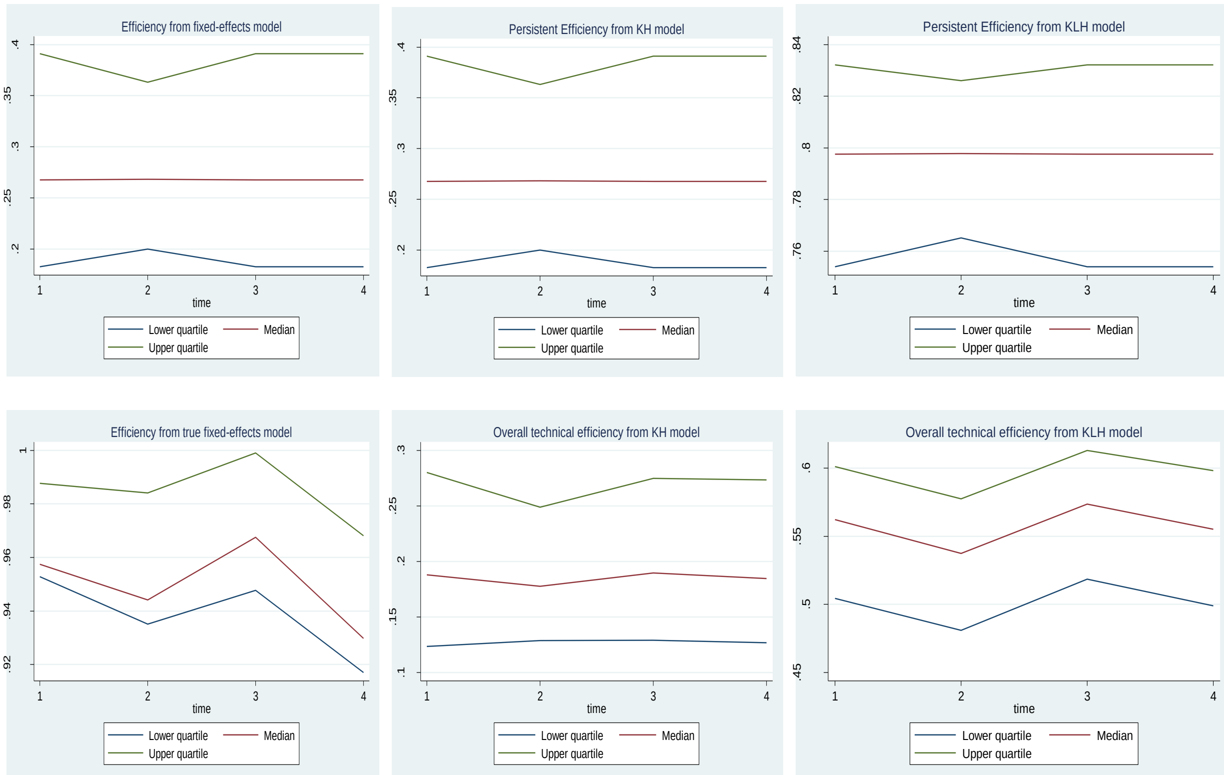


Figure 4.3 The median, first and third quartiles (middle, bottom and top lines) of technical efficiencies

Finally, to compare across models and explore the effects of the estimated models on the ranking order of farmers' technical efficiencies, we estimated Kendall's rank correlation coefficient between efficiency scores (Table 4.6).

Table 4.6 Kendall’s Rank Order Correlation across Models

Models/eff.	Model 1, TE_PTE	Model 2, TFE_TTE	Model 3, KH_PTE	Model 3, KH_TTE	Model 3, KH_OTE	Model 4, KLH_PTE	Model 4, KLH_TTE	Model 4, KLH_OTE
Model 1, TE_PTE	0.998							
Model 2,TFE_TTE	-0.024	1.000						
Model 3, KH_PTE	0.998	-0.024	0.998					
Model 3, KH_TTE	-0.020	0.083	-0.020	1.000				
Model 3, KH_OTE	0.845	-0.013	0.845	0.135	1.000			
Model 4, KLH_PTE	0.998	-0.024	0.998	-0.020	0.845	0.998		
Model 4, KLH_TTE	-0.020	0.083	-0.020	1.000	0.135	-0.020	1.000	
Model 4, KLH_OTE	0.322	0.043	0.322	0.658	0.477	0.322	0.658	1.000

Source: Author’s computations.

The correlation coefficients of persistent efficiencies in the FE, KH and KLH models were positive and high, implying that the models were consistent in generating similar results. Further, correlation coefficients between transient efficiency estimates obtained from all the models were positive, except for the KH and TFE models. These two models had high ranking disagreements. This result is not surprising given the assumptions with respect to time-invariant effects. Transient efficiency estimates from the KLH and TFE models, however, had a low positive correlation while the results of the KH and KLH models were independent and had a positive correlation.

3.2.3 Estimates of Technical Efficiencies across Agro-ecological zone and sub-zones

For an investigation of farmers' performance across AEZs and their position compared to a zone with better efficiency scores, we also give efficiency estimates by AEZs in Table 4.7. Efficiency measures in the models reveal that there were systematic differences between AEZs and AESZs, which show the effects of geographical/climatic conditions on efficiencies.

Table 4.7 Average Efficiency Measures by AEZs and AESZs (NT = 1,648)

AEZs	AESZs	Model 1, TE_PTE	Model2, TFE_TTE	Model 3, KH_PTE	Model 3, KH_TTE	Model 3, KH_OTE	Model 4, KLH_PTE	Model 4, KLH_TTE	Model 4, KLH_OTE
Lowland (mean)	Hot to warm, sub-moist lowland	***0.220***	***0.897***	***0.220***	***0.688***	***0.763***	***0.688***	***0.525***	***0.688***
	Wet-moist cool midland	0.201	0.99	0.201	0.689	0.750	0.689	0.516	0.689
	Sub-moist cool midland	0.412	0.984	0.412	0.690	0.829	0.690	0.572	0.690
	Dry-warm midland	0.319	0.901	0.319	0.693	0.804	0.693	0.557	0.693
Midland(mean)		***0.311***	***0.794***	***0.311***	***0.691***	***0.794***	***0.691***	***0.548***	***0.691***
	Cool highland	0.496	0.948	0.496	0.692	0.839	0.692	0.581	0.692
	Wet-cool highland	0.278	0.971	0.278	0.685	0.786	0.685	0.539	0.685
Highland(mean)		***0.387***	***0.960***	***0.387***	***0.689***	***0.813***	***0.689***	***0.560***	***0.689***

Source: Author's computations.

As one moves from a highland to lowland AEZ, the mean technical efficiency decreased. This suggests that more productive efficiency is associated with an area at a higher altitude where the rainfall and temperature are favorable for cereal production. The low mean score noted in lowland areas can be attributed to several factors that act as constrains in cereal production notably irregularity in rainfall, high temperatures and poor soil characteristics. Further, when we look at the situation across AESZs or through surveyed FAs, estimates of technical efficiencies are the highest in cool highland AESZs and the lowest in wet-moist cool midland AESZs.

4. Conclusion and Policy Implications

This essay investigated persistent and transient productive efficiencies among Ethiopian smallholder cereal farmers in the period 1999-2015. The study employed a 4-error component panel data SF model to distinguish between time-invariant farm heterogeneity and persistent as well as transient productive inefficiencies. The results of this model were compared to the other three panel data SF models in which one of the four components is missing. The models differed in their underlying assumptions of time-variant/invariant efficiencies and their decomposition as well as the separation of technical inefficiencies and farm-heterogeneity effects. Model 2 or Greene's (2005a, 2005b) TFE model disentangled time-varying inefficiencies from time-invariant heterogeneity. Model 4 or the GTFE (Kumbhakar et al., 2014) model; and model 3 or the Kumbhakar and Heshmati (1995) model, distinguished between persistent and transient inefficiencies. We used model 1, or the FE model for estimating time-invariant efficiencies for comparison purposes.

The first-order parameter estimates across models indicate that agro-chemicals, labor, machinery, oxen and livestock significantly enhanced output, suggesting that cereal production in the study area was most responsive to these inputs. Coefficient of time interacted with farmland-area was positive and significant implying that TC was land using. Estimates of time interactions with other inputs were significantly negative, implying factor using TCs for these inputs. This consequently suggests input saving technical changes. However, the overall TC was not neutral because some production factors significantly changed over time. Estimates of production elasticities indicate that each input contributed significantly in enhancing cereal production levels. The results further show that cereal technical efficiency regressed overtime at an increasing rate and exhibited increasing returns to scale.

Efficiency scores across models illustrate significant variations in inefficiency estimates. This confirms the importance of evaluating technical efficiency using distinct specifications and shows that the efficiency estimations were sensitive to model specifications. The essay demonstrated how the results of the classic efficiency evaluation of productive efficiency changed in Ethiopian cereal farming when time-invariant farm heterogeneities and persistent inefficiency were taken into account. The comparison reveals that disregarding heterogeneity distorted the estimation results. The study shows that the classic specifications FE and KH models underestimated efficiency scores because farm-specific effects were treated as inefficiencies. Controlling for heterogeneity and applying Greene's (2005a, 2005b) model, the TFE model improved the accuracy but displayed over-estimated efficiency scores, since persistent inefficiency was compounded in heterogeneity.

Distinguishing between short and long-term inefficiency while controlling for heterogeneity, model 4, the GTFE (Kumbhakar et al., 2014) model, revealed efficiency scores which were in between the aforementioned boundaries. This model improved the accuracy of the estimation, delivered valuable additional information and provided a very dissimilar estimate of overall efficiency levels in the TFE and KH models reducing downward and upward biases.

The empirical results show that cereal farming in the study area was characterized by the presence of both transient as well as persistent productive inefficiencies. However, the GTFE model shows that inefficiency tended to be short-term and transient rather than long-term and persistent. This indicates the existence of operational problems at the farmer or household level.

The existing level of persistent inefficiencies could hinder cereal farmers from achieving better overall production efficiency. The overall implications of the results of the efficiency level analyses indicate that cereal farmers in the study area were highly inefficient and there was a room for improvement. The empirical results of the overall technical efficiency measures from the GTFE model suggest that cereal producing farmers in the study area could increase their production by about 45 percent through more efficient use of inputs. This indicates that most of the farmers were still using their resources inefficiently in the production process and there still existed wide room for improving cereal production by improving the current efficiency levels.

Further, Kendall's rank correlation coefficients showed that the FE, KH and KLH models generated similar and consistent persistent efficiency measures. Further, the correlation between estimates of transient efficiencies obtained from all the models was positive, except for the KH and TFE models. The transient technical efficiency estimates obtained from the KLH and TFE models had low positive ranks, while the results of the KH and KLH models had large positive ranks. The empirical results also show differences in technical efficiency estimates between AEZs and AESZs in the study area, which shows that the impact of agro-climatic conditions on technical efficiency was quite heterogeneous in different AEZs.

These findings are important and can be used to initiate government policy options when planning agricultural policies tailored to supporting various AEZs across the country. Policymakers need to consider whether inefficiency is time-varying and/or time-invariant (persistent) and be aware of whether inefficiency is over-or-underestimated due to heterogeneities while considering some policy options. The study therefore recommends policies that improve measures that reduce inefficiencies, improve the supply of agricultural inputs and that meet the needs of farmers and suit the peculiarities of agro-ecological zones.

Based on the results of this essay some further research work is conceivable. An additional enhancement could be achieved by including a vector with time-variant or time-invariant covariates. This is important as it will allow examining the marginal effects of these variables on inefficiency, which in turn will give an opportunity to deduce policy implications.

References

African Development Bank (AfDB) (2016). *Federal Democratic Republic of Ethiopia: Country Strategy Paper-CSP*, 2016-20.

Aigner, D., C. A. K. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production model. *Journal of Econometrics*, 6(1): 21-37.

Battese, G.E. and T.J. Coelli (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis*, 3: 153-69.

Battese, G.E. and T.J. Coelli (1995). Models for technical inefficiency in a stochastic frontier production function for panel data. *Empirical Economics*, 20: 325-32.

Central Statistical Authority of Ethiopia (CSA) (2014). *Agricultural sample survey (AgSS 2013-2014):* Report on area and production of major crops, private peasant holdings, Meher season, Volume I. Addis Ababa: CSA.

Christensen, L., D. Jorgenson, and L. Lau (1973). Transcendental logarithmic production frontiers. *Review of Economics and Statistics,* 55: 28-45.

Colombi, R., S.C.Kumbhakar,G. Martini, and G. Vittadini(2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis,* 42: 123-36.

Farrell, M.J. (1957). Measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3): 253–81.

Filippini, M. and W.H. Greene (2016). Persistent and transient productive inefficiency: A maximum simulated likelihood approach. *Journal of Productivity Analysis,* 45(2): 187-96.

Food and Agriculture Organization (FAO) (2016). *Federal Democratic Republic of Ethiopia: Country Programming Framework-CPF*, 2016-20. Rome: FAO.

Gebreegziabher, Z., A. Oskam, and T. Woldehanna (2005). Technical Efficiency of Peasant Farmers in Northern Ethiopia: A Stochastic Frontier Approach, in proceedings of the 2nd International Conference on the Ethiopian Economy, Addis Ababa, Ethiopia.

Greene, W. (2005a). Reconsidering heterogeneity in panel data estimators of the stochastic frontier models. *Journal of Econometrics,* 126(2): 269–303.

Greene, W. (2005b). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis,* 23: 7-32.

Heshmati, A., S.C. Kumbhakar, and L. Hjalmarsson (1995). Efficiency of Swedish pork industry: A farm level study using rotating panel data 1976-1988. *European Journal of operational Research*, 80: 519-33.

Heshmati, A., S.C. Kumbhakar, and J. Kim (2017). Persistent and Transient Efficiency of International Airlines. *European Journal of Transport and Infrastructure Research*, forthcoming.

Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt (1982). On the estimation of technical inefficiency in stochastic frontier production model. *Journal of Econometrics,* 19: 233-38.

Karagiannis, G. and V. Tzouvelekas (2009). Parametric measurement of time-varying technical inefficiency: Results from Competing Models. *Agricultural Economics Review*, 10(1): 50–79.

Kassahun, A. (2011). Impact of climate variability on crop production in Ethiopia: Which crop is more vulnerable to rainfall variability? Paper presented at the 9th International Conference of EEA, Addis Ababa, Ethiopia.

Kumbhakar, S.C. (1991). Estimation of technical inefficiency in panel data models with firm- and time-specific effects. *Economics Letters*, 36: 43-8.

Kumbhakar, S.C. and A. Heshmati (1995). Efficiency measurement in Swedish dairy farms: An application of rotating panel data. *American Journal of Agricultural Economics*, 77: 660–74.

Kumbhakar, S.C.,G. Lien, and J.B. Hardaker (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis*, 41(2): 321-37.

Kumbhakar, S.C., H. J. Wang, and A.P. Horncastle (2015). *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*. NY: Cambridge University Press.

Lee, Y. and P. Schmidt (1993). 'A production frontier model with exible temporal variation in technical inefficiency', in H. Fried and K. Lovell (eds), *The measurement of productive efficiency: techniques and applications*. New York: Oxford University Press.

Maurice, J. O., D. Muchai, G. Mwabu, and M. Mathenge (2014). Technical efficiency of Kenya's smallholder food crop farmers: Do environmental factors matter? *Environment, Development and Sustainability*, 16(5): 1065–76.

Pitt, M. and L.F. Lee (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics*, 9: 43–64.

Poudineh R., (2016). *Disentangling inefficiency persistence from the latent firm effect: An application to the Norwegian electricity Networks.* Oxford: Oxford Institute for Energy Studies.

Rashidghalam, M., A. Heshmati, G. Dashti, and E. Pishbahar (2016). Comparison of Panel Data Models in estimating Technical Efficiency, IZA DP, 2016:9807.

Schmidt, P. and R.C. Sickles (1984). Production frontier and panel data. *Journal of Business and Economic Statistics*, 2(4): 367–74.

Tsionas, E.G. and S.C. Kumbhakar (2014). Firm Heterogeneity, Persistent and transient Technical Inefficiency: A generalized True Random Effects model. *Journal of Applied Econometrics*, 29: 110-32.

CHAPTER FIVE

Analysis of Factors Affecting Persistent and Transient Inefficiency of Ethiopia's Smallholder Cereal Farming

Abstract

This essay explains persistent and transient inefficiency effects among smallholder cereal farmers in Ethiopia using household-level panel dataset for 1999-2015. It uses a 4-component stochastic frontier model with determinants of inefficiency and uses a mixed efficiency analysis approach in two steps. First, it estimates persistent and transient inefficiency scores and simultaneously explains their differentials. Second, in a two-stage approach it explains the overall inefficiency effects. Inefficiency effects models reveal that most farmer-specific characteristics, adaptation strategies, agro-ecological and climatic factors influence farming efficiencies with different magnitudes. Transient efficiency is enhanced by gender, household size and number of plots, while it is negatively influenced by age, secondary schooling and temperature variations. Persistent inefficiency is negatively influenced by altitude and ecological factors while overall efficiency is enhanced by farm size, gender, household size and remittances; improved adaptation strategies; and weather and ecological factors. It is negatively influenced by credit use, age, territory, schooling, off/non-farm activities and extreme weather variations. The essay also shows that omission of weather factors from specification affects not only reduce the model's precision, but also results in biased inefficiency scores and estimates of determinants. These findings are important and can be used to initiate policy options when planning climate change adaptation strategies and agricultural policies. It also discusses policies that advance input supply and sustain improved adaptation strategies and which are suitably designed to suit the needs of farmers and agro-ecological zones' peculiarities to enhance short-term and long-term productive efficiencies of cereal farming in Ethiopia.

Keywords: Stochastic frontier, agro-ecology, cereal farming, persistent and transient inefficiency, panel data, Ethiopia.

JEL Classification Codes: C23, D21, D23, D24, O13, Q12.

1. Introduction

Studying the sources of increased production, examining the extent of inefficiency and identifying the sources of inefficiencies are important instrument for informing policymakers. Agriculture plays an important role in overall economic growth in Ethiopia (the World Bank, 2010), and it has significant spillover effects on the other sectors of the economy as well. Ethiopia's agriculture is largely characterized by rainfall dependence and is dominated by smallholder production mainly for subsistence.

Agriculture accounts for 38.5 per cent of the country's gross domestic product, up to 81 per cent of total export earnings and provides livelihood to more than 83 per cent of the population (AfDB, 2016). Despite frequent droughts and traditional farming practices in the country, Ethiopia has huge agricultural potential due to its ample arable land, an abundant workforce and diverse AEZs (Beyan et al., 2013). However, despite the widely believed view of the central role of agriculture in economic transformation, the sector has not performed as per expectations. As pointed out in the Growth and Transformation Plan (GTP I) document (MoFED, 2010) the sector, among others, is facing challenges imposed by climate change, high population pressure and severe environmental degradation. The sector is characterized by inefficiencies and low productivity in which cereals have shown a steady low-growth rate in the last two decades. Hence, being an agriculture dependent country with limited capacity for developing and adopting new technologies, increasing production and enhancing farming efficiencies with the existing technologies is not a matter of choice but is instead a must for Ethiopia.

In his classic hypothesis, Schultz (1964) argued that traditional farmers in developing economies are 'poor but efficient'. He argued that given a long enough period of time to learn their production processes they will identify their respective optimal input and output bundles. This famous hypothesis has made researchers and policymakers believe that increase in production and hence efficiency cannot be realized with the given resources and technologies and the focus should be on investing in new technologies to shift the frontier upward. Yet, countless empirical studies have refuted Schultz's claim, finding the existence of widespread inefficiencies among smallholder farmers and recommending ways in which these farmers can reallocate their resources for redressing their technical inefficiency levels. Recent research in the area reveals that inefficiencies in production can arise because of different reasons - time-invariant production heterogeneities (such as land quality) and the varying effects of climatic factors – and these cannot be eliminated by the institutions/farms themselves. However, primarily due to data limitations only a few studies have controlled for these time-invariant effects which potentially affect production.

Moreover, recent efficiency studies also question the accuracy of results of the classic models due to the sensitivity of efficiency results to the way they are modeled and interpreted mainly when panel data is used (Kumbhakar et al., 2014). When panel data is available, productive efficiency can be seen as composed of persistent and transient components which are not captured distinctively by the earlier models. Thus, long term factors exist which cannot be altered by the farmers and should not be ruled out from the efficiency term. Recent efficiency studies, therefore, recommend advanced efficiency modeling that allows distinguishing between long-term fixed factors (heterogeneity) and equally long-term, but alterable persistent inefficiencies, while accounting for the other inefficiency components. While the distinction of two long term factors allows more accurate estimations, the additional separation of the two inefficiency components permits a more elaborate evaluation of policy implications because both components convey different types of information. When thinking of appropriate policy recommendations for the sector, it is therefore essential to distinguish between the influence-able short and long-term efficiencies, while controlling for exogenous factors. However, technical efficiency scores obtained from efficiency estimating models alone have little use for policy implications and management purposes if the empirical studies do not investigate the sources of the inefficiency. Proponents of determinants of technical efficiency offer insights into key variables for making policies for optimal resource utilization and this in turn has implications for improving productivity and livelihood options.

Several studies have analyzed efficiency of crop production in Ethiopia; however, only a few focus on linking productive efficiency with climate/weather effects or to its variations. Most previous studies have paid relatively little attention to assessing the influence of agro-eco-climatic factors and adaptation strategies on farm efficiency in the country. More importantly most studies in the area ignore farm-heterogeneity and fail to capture the distinctively transient and persistent efficiency components. Therefore, a comprehensive analysis with the newly developed efficiency model's specifications including sources of inefficiency differentials is overdue.

This essay aims to bridge this gap in literature by considering a 4-component panel data stochastic frontier model to estimate and explain persistent, transient and overall technical inefficiencies while controlling for time-invariant farm-heterogeneities in Ethiopia's smallholder cereal farms using a household-level panel dataset for 1999-2015. It pays particular attention to incorporating farmer-specific characteristics, climate change adaptation strategies and weather and agro-ecological factors in explaining the effects of productive inefficiencies.

The econometric opportunity to include both arguments (time-invariant heterogeneities and persistent inefficiency) has emerged just recently. Colombi et al., (2014) established the new specification to separate short and long term perspectives on efficiency changes, while controlling for heterogeneity using a 4-error component panel data SF model. While this novel specification has been used in selected areas (see, for example, Filippini et al., 2016 for an application in electricity distribution and Heshmati et al., 2017 for an analysis of international airlines) it was only recently applied to the agricultural sector by Kumbhakar et al., (2014) using data on grain farmers in Norway. Lai and Kumbhakar (2016) extended this model to accommodate factors that explain both persistent and transient technical inefficiencies. To the best of the researcher's knowledge, this has rarely been applied in general and certainly not to Ethiopian agriculture; thus this study is the first to use the model and extend it to accommodate factors that can explain inefficiency components, including the overall technical inefficiency effects.

The study contributes to efficiency literature as it is the first to use a 4-error component panel data SF model and extends the model to accommodate factors that can explain inefficiency components in Ethiopia's crop farming. It thus helps in identifying if inefficiencies have been persistent overtime or they are time varying in the country's cereal farming by distinguishing farm heterogeneity effects from inefficiencies. In particular, the essay estimates the production frontier with and without the weather variables' specifications to examine the effects of omitting weather factors in model specifications on technical efficiency estimates and correlates of technical inefficiency effects. Moreover, it also considers technical inefficiencies from both specifications (with and without the weather factors) and campers the results using different regression techniques. Hence, this essay contributes to a modeling approach in which the inclusion of climate variables improves the precision with which one can estimate and explain technical inefficiencies. The essay is also unique in the methods that it uses to explain persistent, transient and overall technical efficiencies. It uses a mixed efficiency analysis approach in two steps. In addition to the usual farmer-specific characteristics in similar studies on Ethiopia this study incorporates climate change adaptation strategies and weather and agro-ecological factors as factors that explain inefficiency. Thus, it contributes to identifying a number of key policy-relevant technology shifters by examining their effects on inefficiency components from which it draws policy implications. Overall, this study has a significant contribution to the limited literature on agro-eco-climatic factors and adaptation strategies on productive efficiency in Ethiopia in particular, and in least developed countries (LDCs) in general.

The remainder of this essay is organized as follows. Section 2 provides a short overview of recent empirical literature on panel data SF models. It also lists the methods and dataset used in the analysis. Section 3 provides estimation results and discusses the empirical findings. The last section gives concluding remarks and policy implications.

2. Methodology and Data

2.1. Review of Stochastic Frontier Production Models

Following the pioneering work of Farrell (1957) various modifications and improvements have been made to the measurement of production efficiency. Aigner and Chu (1968) translated Farrell's frontier into a production function and later Aigner et al., (1977) suggested the SF approach. This approach deals with stochastic noise and permits statistical tests of the hypothesis pertaining to the production structure and the degree of inefficiency. As a result, SFA has been considered a standard approach for evaluating efficiency in a variety of research areas. While the initial studies were limited to cross-sectional data, the utilization of panel datasets soon became customary. The use of panel data considerably enriched the econometric analyses of SPF models and has several advantages over cross-sectional data. According to Schmidt and Sickles (1984) and Heshmati et al., (1995) panel data offers a more efficient estimation of the SPF model and provides consistent estimators of farm inefficiencies. Panel data also permits the simultaneous identification of stable long-term (persistent) and varying short-term (transient) technical inefficiency components.

The first panel data versions of the standard 1990s SPF models can be written as:

$$(1) \qquad y_{it} = x_{it}\beta + \varepsilon_{it} - \tau_{it} \;= x_{it}\beta + \varphi_{it}$$

where, $i = 1, \ldots, n$ denotes observations and $t = 1, \ldots, T$ denotes time period. In a SPF model, the outcome variable y_{it} is the logarithm of output, x_{it} is the row vector of constant logarithms of the input variables and possibly other observed covariates that include environmental variables that are not primary inputs but nonetheless affect output. β is a vector of unknown parameters to be estimated; φ_{it} is the error term composed of two independent elements such that: $\varphi_{it} = \varepsilon_{it} - \tau_{it}$. The idiosyncratic component ε_{it} is the noise term, assumed to be *i.i.d.* normal with zero mean; and variance σ_{ε}^{2}, captures random variation in output resulting from factors outside the control of the farm as well as measurement errors and left-out explanatory variables. Similarly, the one-sided component $\tau_{it} \geq 0$ reflects time-varying inefficiency relative to the SF of the i^{th} firm in year t, assumed to be identically independently distributed *(i.i.d.)* as half normal, that is:

$$\tau_{it} = |\mathrm{T}_{it}|, \ where\ \mathrm{T}_{it} \sim i.i.d.\ N^{+}(0, \sigma_{\mathrm{T}}^{2}).$$

A number of SPF models in panel data have been developed successively giving rise to alternative measures of technical inefficiency. Kumbhakar and Heshmati (1995) interpreted $\tau_{it} \geq 0$ as time-varying technical inefficiency and added an extra component $\eta_i \geq 0$ to represent persistent inefficiency. The persistent component is consistent with the models used in the 1980s (Battese and Coelli, 1988; Schmidt and Sickles, 1984), whereas the time-varying component is consistent with the models developed in the 1990s (Battese and Coelli, 1992).However, recently a philosophical question about the way of interpreting η_i has been raised -- should one view it as persistent inefficiency as in Kumbhakar and Heshmati (1995) or as firm-heterogeneity that captures the effects of (unobserved) time-invariant covariates that have nothing to do with inefficiencies as in Greene (2005a, 2005b). Badunenko and Kumbhakar (2016) state that several authors have addressed this issue and give a number of explanations. More recently Colombi et al., (2014) and Kumbhakar et al., (2014) presented the first panel data SPF model including both arguments. They introduced a model that accounts for heterogeneity and persistent inefficiency by splitting the error term into four components -- persistent and transient inefficiency, random farm-effects and noise.

The separation of persistent inefficiency from transient inefficiency is important because they have different policy implications. Transient inefficiency is interpreted as short-run technical inefficiency associated with changes in managerial skills or disruptions resulting from the adoption of new technologies that can be changed in the short-run. By contrast, persistent inefficiency can be seen as long-run technical inefficiency due to structural or institutional factors which evolve slowly overtime. Since persistent inefficiency is time-invariant, it can only be changed in the long-run through some restructuring. While long-run technical inefficiency and individual farm unobserved heterogeneity are both time invariant effects, a major difference between them is that the latter is always beyond the control of decision makers (for example, the geological make-up of a country and its other physical features).

In efficiency analyses, efficiency scores obtained from efficiency estimating models have little use for policy implications and management purposes unless the empirical work includes an analysis of the sources of inefficiency. Given that in reality farm efficiencies (both persistent and transient) systematically differ across farms and over time, a model that can produce not only the magnitude of these inefficiencies but can also explain their systematic differences in terms of some covariates are needed (Lai and Kumbhakar, 2016). Moreover, if the inefficiency component is purely random, farmers do not know how to improve their efficiency irrespective of whether the public provides incentives or not. Further, if the persistent inefficiency component of a farm is high, the farm is likely to stay inefficient unless there is major restructuring (change in the management, for example). Perhaps if inefficiencies are explained by some covariates, then the farmers can change their inefficiency levels by changing those covariates which are specific to their inefficiency components.

Models for Assessing Inefficiency Effects

Most of inefficiency effects models in existing literature are subject to controversies. In this regard, despite the fact that the approaches vary to some extent as per the methodologies that they employ, the most commonly followed procedure is what is usually referred to as a one-stage approach or the two-stage approach. Some authors like Parikh and Shah (1994) estimated SPFs to predict firm/farm level (in) efficiency indices and then regressed these predicted efficiencies on firm/farm specific variables to explain variations in inefficiencies between firms in an industry. To overcome inconsistencies in assumptions regarding the independence of inefficiency effects in this two-stage estimation procedure, Kumbhakar et al., (1991), Reifschneider and Stevenson (1991)and Huang and Liu (1994) proposed a single-stage SF in which the inefficiency effects are expressed as an explicit function of the vector of firm/farm specific variables and a random error. They suggest a specific model (under SPF models) that allows the estimation of inefficiency scores and simultaneously explains inefficiency effects. Battese and Coelli (1995) generalized Huang and Liu’s (1994) model to allow for panel data, extending the earlier approaches and suggested that technical inefficiency effects, u_{it}, could be replaced by a function of explanatory variables that are supposed to explain inefficiency directly incorporated into the MLE under the one-stage approach SFA models. These models allow the technical inefficiency parameter and hence technical efficiency to vary across time in a potentially different, but predictable, manner across firms/farms.

This essay uses the mixed efficiency analysis approaches. Firstly, it uses a one-stage SFA approach by extending the 4-error component model to accommodate factors that can explain persistent and transient inefficiencies. Under this approach we estimated the persistent technical efficiency (PTE) and the transient technical efficiency (TTE) scores, and simultaneously used the respective inefficiency effects model and computed the marginal effects of the determinants of each type of inefficiency. Meanwhile, we used a two-stage approach to explain the overall technical efficiency (OTE) differentials. Here the OTE scores are estimated as a product of PTE and TTE from the first stage efficiency estimates and successively regressed on the covariates at the second-stage using panel data models. The two-stage approach in SFA has been criticized by several authors due to its inconsistency in the assumption of inefficiency parameters' distribution.

However, as underlined by Reinhard et al., (2002), a two-stage procedure can consistently be used as long as the efficiency scores are calculated from a particular kind of fractional or proportional data generating process (DGP) from the first-stage parameter estimates instead of being estimated econometrically at the first stage. Hence, by applying the two-stage approach at the first-stage we obtained the persistent, PTE and TTE scores econometrically. Then we generated the OTE scores as a product of PTE and TTE scores and used them as a dependent variable in the second-stage regression.

Regarding second-stage regression techniques, a researcher can choose to use the desired regression techniques as discussed by Hoff (2007) and Banker and Natarajan (2008), particularly when the efficiency scores are not generated by a censoring process but are fractional data. For instance, following Reinhard et al.'s (2002) procedure, Madau (2011) used a MLE technique to estimate inefficiency effects parameters in his second-stage regression. Similarly, MacDonald (2008) estimated robust standard errors OLS parameters in his second-stage regression and argued that the Tobit estimation was inappropriate when efficiency scores were not generated by a censoring DGP. He explains that if efficiency scores are not censored, MLE (Tobit) and OLS estimates are identical; but, MLE does not give appropriate marginal effects of the estimation. In contrast, he proposed OLS as an unbiased and consistent estimator provided heteroscedasticity tests can be validly undertaken and parameter estimates with robust standard errors can thus be obtained.

Moreover, in line with MacDonald's work, most of the time efficiency scores from the SPF models are bounded between 0 and 1, that is $(0 < \phi < 1)$. That is, there are no farm units for which efficiency (ϕ) is one or farmers who achieved an efficiency score of zero. This is because the SPF model allows comparison of DMUs operating with similar technologies and hence most of the time there is no farm which is 100 per cent (in) efficient as SFA is relative to the possible frontier technology. As a result, the distribution of efficiency scores is not censored, that is, there are no efficiency observation(s) with $\phi = 0$ and/or 1.

Consequently, in line with Lai and Kumbhakar (2016) this essay uses the 4-error component SPF models to estimate and explain persistent and transient inefficiency components and employs

Reinhard et al., (2002) and MacDonald's (2008) recommendations to explain overall technical inefficiency. Such a model not only provides estimates of persistent and transient inefficiency but also generates marginal effects of the determinants of inefficiencies. The marginal effects give estimates of inefficiency changes due to changes in the corresponding factors (which are often policy variables). Such a comprehensive analysis (separation of inefficiency components and identification of their determinants) is important for providing evidence to the government whose objective is to ensure that the farmers operate as efficiently as possible.

2.2 Model Specifications and the Estimation Procedure

Colombi et al., (2014) and Kumbhakar et al., (2014) among others decomposed the error term in Equation1 into $\tau_{it} = \eta_i + u_{it}$ *and* $\varepsilon_{it} = \mu_i + \upsilon_{it}$ to obtain a4-error component SPF model:

$$(2) \qquad y_{it} = x_{it}\beta + \varphi_{it} = f(x_{it};\beta) + \mu_i + \nu_{it} - \eta_i - u_{it}$$

where, μ_i is random farm-effects which captures farms' heterogeneity (Greene, 2005a, b); $\eta_i \geq 0$ is long-run (persistent) inefficiency; $u_{it} \geq 0$ captures time-varying inefficiency; and v_{it} is the random noise term. They also derived a closed form expression of the likelihood function of the composed error term 'φ_{it}' based on the assumption that each component is distributed independently and identically, and that the components are also independent of each other. More specifically, they assumed $\mu_i \sim$ i.i.i. $N(0,\sigma_{\mu}^2)$, $v_{it} \sim N(0,\sigma_v{}^2)$,while the non-negative components are both assumed to be half-normal, truncated at zero from below, that is, $\eta_i \sim N^+(0,\sigma_\eta{}^2)$ and $u_{it} \sim$ i.i.d. $N^+(0,\sigma_u{}^2)$.

This model is an extension of the true fixed-effects (TFE) or true random-effects (TFE) models proposed by Greene (2005a, 2005b) respectively. This model can be estimated assuming that either the inefficiency component (u_{it}) is a fixed parameter that directly influences the dependent variable (the fixed-effects model) or assuming that the inefficiency component (u_{it}) is a random variable that has a correlation with the independent variables (the random-effects model).The model is known as the 'Generalized TFE', labeled as the GTFE model in case one considers a FE model or 'Generalized TRE', labeled the GTRE model for a RE model in several recent studies.

There are several ways to introduce the determinants of inefficiency in a SPF model. Perhaps the simplest way is to make the variance parameters of inefficiency terms (η_i and u_{it}) functions of the determinants respectively. Accordingly, for persistent and transient inefficiency effects introducing the neutral SF model, we assume $\eta_i \sim N^+(0,\sigma_\eta{}^2(z_i))$ and $u_{it} \sim N^+(0,\sigma_u{}^2(z_{it}))$, that is, the technical inefficiency parameter is related to a vector of farmer-specific variables subject to statistical errors. To ensure that $\sigma_\eta(z_i)$ and $\sigma_u(z_{it})$ are positive, we re-parameterized

$\sigma_\eta(z_i) = \exp(\lambda^T z_i)$ and $\sigma_u(z_{it}) = \exp(\delta^T z_{it})$ where the z_i and z_{it} variables are determinants of persistent and transient inefficiency respectively.

Multi-step Estimation Procedure

To estimate the parameters of SPF and the efficiency scores from a model in Equation2, we used a fixed-effects model which allows addressing the influences of omitted variables and provides consistent estimators (Baltagi, 2008). We employed a multi-stage ML estimation method (due to Kumbhakar et al., 2015). To implement this multi-step procedure the model in Equation2 is rewritten as:

$$(3) \qquad y_{it} = \alpha_0^* + f(x_{it}, w_{it}; \beta) + \alpha_i + \omega_{it}$$

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

With this specification α_i *and* ω_{it} have zero mean and constant variance. This model can be estimated in three steps: In step 1 the standard fixed-effects panel regression is used to estimate the coefficients β as well as the predicted values of α_i and ε_{it} .

In step 2, the prediction of ε_{it} is exploited to estimate transient (in) efficiency using the standard SF technique and the corresponding inefficiency effects parameters simultaneously. This procedure predicts the time-varying residual technical inefficiency index following Jondrow et al., (1982) or residual (transient) technical efficiency (RTE) index (and marginal effects) following Battese and Coelli (1988). In step 3, following a similar procedure as in step 2, η_i is used to obtain the PTE estimates and the corresponding inefficiency effects parameters simultaneously. The PTE index (and marginal effects) can be estimated using the BC formula. Lastly, as mentioned in Kumbhakar et al.,(2015), the OTE estimate is acquired from the product of transient or residual and persistent technical efficiency estimates, that is, $OTE_{it} = PTE_i \times RTE_{it}$

2.3 The Empirical Models

2.3.1 The Stochastic Production Frontier Model

The production function $f(x_{it}; \beta)$ in Equation2 is specified using a flexible translog functional form to approximate the underlying technology. The translog specification is preferred and allows an interaction of inputs, non-constant elasticity of substitution and provides valuable information from the interaction terms. To examine the effects of omitting weather factors in the model's specifications in technical inefficiency estimates and correlates of technical inefficiency effects, we estimated the production frontier with and without the weather variables.

Thus, assuming multiplicative separability of X_{it}, W_{it}, and Z_{it} to conserve degrees of freedom in estimating the 'full' specification – production frontier with the weather variables (that is, $f(x_{it}, w_{it}; \beta)$) the 'full' specification has the form:

$$y_{it} = x_{it}\beta + \varphi_{it} = f(x_{it}, w_{it}; \beta) + \mu_i + \nu_{it} - \eta_i - u_{it} \quad ; \quad \text{i.}\, e.$$

$$(4a) \qquad y_{it} = \beta_0 + \sum_{j=1}^{7} \beta_j \ln X_{jit} + \beta_t T_t + \frac{1}{2}\left(\sum_{j=1}^{7}\sum_{h=1}^{7} \beta_{jh} \ln X_{jit} \ln X_{hit} + \beta_{tt} T_t^2 \right) + \sum_{j=1}^{7} \beta_{jt} \ln X_{jit} T_t + \sum_{k=1}^{4} \beta_k \ln W_{kit} + \mu_i + \nu_{it} - \eta_i - u_{it}$$

And the traditional or 'short' specification – production frontier without the weather variables, (that is, $f(x_{it}; \beta)$) may be written as:

$$y_{it} = x_{it}\beta + \varphi_{it} = f(x_{it}; \beta) + \mu_i + \nu_{it} - \eta_i - u_{it} \quad ; \quad \text{i.}\, e.$$

$$(4b) \qquad y_{it} = \beta_0^* + \sum_{j=1}^{7} \beta_j^* \ln X_{jit} + \beta_t^* T_t + \frac{1}{2}\left(\sum_{j=1}^{7}\sum_{h=1}^{7} \beta_{jh}^* \ln X_{jit} \ln X_{hit} + \beta_{tt}^* T_t^2 \right) + \sum_{j=1}^{7} \beta_{jt}^* \ln X_{jit} T_t + \mu_i + \nu_{it} - \eta_i - u_{it}$$

where, the outcome variable y_{it} is the logarithm of output representing the normalized output measure of farmer i, $i = 1,2,...,N$ and time period t, $t = 1,2,...,T$. The function $f(.)$ describes the output technology; X_{it} represents a vector of the normalized conventional production inputs and W_{it} is a vector of weather variables. T is the time trend which is a proxy for the exogenous rate of technological change; β represent unknown parameters to be estimated. All other terms maintain their previous definitions as in Equation2.

2.3.2. The Inefficiency Effects Models

To specify the determinants of persistent and transient inefficiencies we make the variance parameters of u_{it} and η_i functions of the determinants respectively. That is, the inefficiency terms η_i and u_{it} as explained in Equation2 are expressed as:

$$(5a) \qquad u_{it} = \delta_0 + \sum_{m=1}^{M} \delta_m Z_{mit} + \sum_{k=1}^{K} \delta_k E_{kit} + \delta_t T + \delta_{tt} T^2 + w_{it} \qquad \textit{and} \qquad \eta_i = \lambda_0 + \sum_{l=1}^{L} \lambda_l P_i + \varphi_i ,$$

To explain the OTE differentials we use the following specification at the second-stage regression:

$$(5b) \qquad \ln u_{it} = \alpha_0 + \sum_{m=1}^{M} \alpha_m Z_{mit} + \sum_{k=1}^{K} \alpha_k E_{kit} + \alpha_t T + \alpha_{tt} T^2 + \sum_{l=1}^{L} \alpha_l P_i + \xi_{it}$$

where, i denotes farmers and t the time period; Z_{it} denotes the vector of farmer-specific characteristics and adaptation technologies and time-varying variables; and E_{it} denotes the vector of weather factors. P represents vector of independent (time-invariant) variables assumed to influence persistent technical inefficiency. The terms δ, λ and α are unknown parameter vectors to be estimated including the constant parameters. Whereas w_{it}, ξ_{it} and ϕ_i are the corresponding error terms that represent the statistical noise that are independently and identically distributed, whose distributions are truncated from below at the variables truncation point, that is, with $\omega_{it} \sim N(0, \sigma_w^2)$, $\phi_i \sim N(0, \sigma_\phi{}^2)$ and $\xi_{it} \sim N(0, \sigma_\xi{}^2)$. T is the time trend. Battese and Coelli (1995) included time variables in SPF and inefficiency equations to account for both technical change and time varying technical inefficiency effects respectively. The trend variable in Equation4accounts for Hicks neutral technological change while the trend variable in inefficiency in Equation 5 takes into account inefficiency changes that occur during the period considered. Moreover, the square of weather variables and the trend term is also included in the specification to account for non-linearity effects. Hence, in the one-stage approach, all parameters – frontier production in Equation 4b and inefficiency effects in Equation 5aare estimated simultaneously. The OTE effects model in Equation 5b is estimated using panel model techniques in the second-stage regression using a combination of explanatory variables used in the TTE and PTE effects models.

2.4 Data Source and Classification

Data Source: The data source for this essay is Ethiopian Rural Household Survey (ERHS) data collected from randomly selected farm households in rural Ethiopia. It includes farm production and economic data collected at 5-year intervals from local farmers associations (FAs) that were selected to represent the country's diverse farming systems. The first four waves of the survey were conducted in collaboration with the Department of Economics, Addis Ababa University and the International Food Policy Research Institute (IFPRI). The last round was extended to form a sub-sample from the original respondents covering eight FAs following a similar strategy. This comprised of 503 farm households and was conducted by this researcher in 2015 with financial support from the Environment for Development (EfD) initiative at the University of Gothenburg, Sweden.

The dataset was comprehensive addressing households' demographic and socioeconomic characteristics; production inputs and outputs; access to institutions; and climate change adaptation mechanisms. Moreover, important secondary data such as the FAs' geographical location and elevation (altitude) and metrological data were obtained from the Ethiopian Meteorology Authority. The meteorological data includes monthly average observations of rainfall and maximum and minimum temperatures in 1994-2015 collected in stations close to the study villages. Consequently, this study employed data from 4-survey rounds (1999, 2004, 2009 and 2015) covering eight FAs, forming a partially balanced panel of 446 households. The 1994 survey was excluded as it does not have most of the important variables needed for the analysis.

Variables: The production (output) variable contains the value of cereal output (*Y*), which combines aggregate output of cereal crops measured in thousands of Ethiopian birr (ETB) used as a dependent variable for the SF function. The explanatory variables for frontier function include seven different conventional inputs: labor employed measured in man-day units (MDUs); cereal sown farmland in hectares; amount of fertilizers used in kilograms; agricultural machinery implements in ETB; livestock ownership in tropical livestock units (TLUs) as a proxy for wealth and livestock asset endowments; agro-chemicals in ETB including pesticides, herbicides and insecticides; and oxen as animal draft power in number of the oxen owned as these are mainly used in traditional farming during land preparation and harvesting periods. To capture technical changes (shift in the production function) we included the time trend variable (time) - a positive (negative) coefficient on which will reflect technical progress (regress) over time while the squared trend captures the non-linear shift in the production function over time. We define the time trend variables as time $t = 1,\ldots, 5$; for years 1999,…,2015.

In addition to these input and output variables, we also included two sets of variables on *Z* variables as determinants of inefficiency. More specifically, we used the first set of variables -- the time-invariant but location-specific factors as determinant of persistent inefficiency. The second set of variables includes time-varying farmer-specific characteristics while adaptation technologies and agro-ecological and climatic factors are used as determinants of transient inefficiency. The time trend variable is also included in transient inefficiency effects variables to capture temporal variations in transient inefficiency, ceteris paribus. All monetarily measured variables were transformed to fixed ETB prices. The input variable ‘seeds’ was excluded from the analysis due to lack of information.

Climatic/weather variables: The climatic dataset contains annual mean precipitation (PRECIP) measured in millimeters (mm) and annual maximum temperature (ATEM) measured in degree Celsius (^{o}C) and their variability (measured by their coefficients of variation from the corresponding means). According to climate model simulations, climate change causes variations in frequency and intensity of precipitation (Chou et al., 2012). These authors argue that the amount of rainfall, that is, its intensity (quantity), rainy-day frequency (how often it rains) and maximum temperature are important factors to consider when analyzing the sensitivity of agricultural production due to climatic variability particularly in rain-fed regions. ATEM is based on two indicators: the Monthly Mean Temperature (MMT) and the Diurnal Temperature Range (DTR). MMT is calculated as the median between the observed monthly maximum and minimum temperatures whereas DTR is the difference between the monthly maximum and minimum temperatures. Finally, ATEM is calculated by adding half of DTR to MMT (Harris et al., 2014) and is used as a measure of extreme temperature because it captures temperatures at a time when evaporation is higher. In addition to the mean of the weather variables, following Barnwal and Kotani (2013), we used the intra-annual standard deviation (coefficient of variation), which is a measure of monthly deviation within a year to capture variability. Finally, annual climatic data for the weather variables in the study were calculated as the 12-month average (Harris et al., 2014). Summary statistic of these variables are given in Tables 5.1and 5.2.

3. Empirical Results and Discussion

3.1. Descriptive Discussion

Because our interest is in doing a panel data analysis of smallholder farmers' cereal production, we excluded data from a few survey years as well as observations with missing data, leaving us with a partially balanced panel of 446 cereal farmers for estimation from an original sample of 503 farmers. Sample descriptive statistics are presented in Tables 5.1 and 5.2 for the relevant variables.

Table 5.1 presents descriptive statistics for the continuous variables with their trends over time -- growth rates of cereal production and input variables. As is evident from the table, there was relatively little use of cultivated farmland which is typical of smallholders, cereal farming and considerable variations in the amount of fertilizers, agro-chemicals, machinery and farm labor use patterns, as well as weather conditions. Farmers' real value of output captured in thousands of Ethiopian birr (ETB) was used as a dependent variable in the stochastic frontier models. As shown in Table 1, its mean was about 11, 313 birr ranging from 83 to 444,810 birr for the study period. The mean of cereal output produced during the period was about 1,952kg ranging between 34kg and 51,100kg per farm household during the study period. The farmers cultivated cereals on average on about 1.8 hectares and used 342.6 MDUs of labor. Fertilizer application was minimal with an average of 116.1kg per farm household while the expenses on agro-chemicals were on average 133.9ETB. The farmers spent 336.27ETB for agricultural machinery used per farm household. Average livestock ownership was 6.5TLUs and average oxen ownership was around 1.8 oxen meaning that farms on average owned about two oxen ranging from no ox (which constituted 20 per cent) to nine oxen per farm household.

The sample statistics show that production and input use except for the number of oxen had positive trends over time in the study area.An increase in cereal production during the study period was seen at a rate of about 0.261 per cent per annum. The aggregate input use increased at an average annual rate of 0.29 per cent. Most of the aggregate input growth is associated with agro-chemicals and the amount of fertilizers used at an average annual rate of 0.37 and 0.19 per cent respectively.

Male-headed households constituted 76 per cent (hence there were only 24 per cent female-headed households) of the total sample. Average household age was 51.17 years with minimum and maximum of 18 and 103 years while household size ranged from one to18 members, with a mean of approximately six members. The two interaction variables: total farm size (interaction between area cultivated and number of plots) and population pressure (the ratio of the size of productive/working household members to the cultivated farm size) averaged 3.45 and 0.63 respectively.

Table 5.1 Summary Statistics of Continuous Variables (NT = 1,648)

Variable	Mean	Std. Dev.	Min	Max	Growth rate
Stochastic frontier variables					
Output produced(kg)	1,952.251	2,681.805	34.000	51,100.000	0.261
Fertilizers used(kg)	116.100	138.850	0.080	1,400.000	0.131
Agro-chemicals(ETB)	133.900	447.170	0.010	8,560.000	0.370
Farm labor (MEU)	342.620	714.210	3.000	8,333.880	0.033
Machinery(ETB)	336.690	1,775.800	0.500	36,540.000	0.192
Livestock units (TLUs)	6.490	5.930	0.001	58.800	0.049
Number of ploughing oxen	1.770	1.330	0.010	9.000	-0.010
Cultivated land area (HEC)	1.750	1.280	0.020	11.000	0.055
Weather factors					
Annual average rainfall (PRECIP)(mm)	82.055	26.881	47.467	145.958	-0.029
Annual Average minimum temperature(°C)	10.921	2.983	6.358	17.217	0.023
Annual Average maximum temperature(°C)	26.137	4.134	19.908	33.014	0.004
Annual Average temperature(°C)	18.483	3.446	13.158	23.958	0.009
Annual maximum temperature (ATEM)(°C)	17.120	2.560	13.270	21.550	0.006
Rainfall coefficient of variations	0.015	0.008	0.0058	0.033	-0.025
Temperature coefficient of variations	6.052	3.034	1.846	14.851	0.214
Inefficiency effects variables					
Household's size	5.830	2.670	1.000	18.000	-0.012
Number of plots cultivated	3.620	2.440	1.000	16.000	0.026
Total farm size	3.450	4.440	0.030	61.250	0.071
Population pressure	0.634	0.797	0.003	11.000	0.043
Household head's age(years)	51.169	15.359	18.000	103.000	
Altitude (m)	1,948.432	482.535	1351	2750	
Distance to closest market center(km)	8.220	7.000	0.250	24.000	
Time = 1,…, 5; for years 1999,…,2015	2.540	1.150	1.000	4.000	

Source: Author's calculations.

Looking at the weather variables in the study area as shown in Table 1, we find that in general for the four panels the average annual rainfall (PRECIP) was 82.1 mm that varied between 47.5 and 145.6mm. Average maximum temperature was 26^{o}C that varied from 19.9 to 33.01^{o}C and average minimum temperature was 10.92^{o}C, fluctuating from 6.36 to 17.22^{o}C while the average temperature was 18.48^{o}C ranging from 13.16^{o}C to 23.96^{o}C. When we see the annual weather variable trends, climate/weather data shows a significant declining trend of annual average rainfall and warming trends in the temperature variable. Average rainfall distribution declined over time at a rate of 0.029 mm annually and average temperature distribution increased at a rate of 0.009^{o}C per cent annually, while annual maximum temperature (ATEM) increased at a rate of 0.006^{o}C annually during the study period.

A total of 38.3 per cent of the farmers reported contact with extension agents (had 1-4 contacts per month, that is, on average 1.6 times). Extension participation was represented by extension visits per week/month in which the farmers reported contact with extension agents. However, we used a dummy variable that assigned a value of 1 if the farmer got agricultural advisory services, instead of number of contacts which might exaggerate the percentage of households who participated in extension programs. Accordingly, about 38.3 per cent of the farmers reported seeking agricultural advisory services. Almost half (52.2 per cent) of the sampled farmers had access to credit.

Table 5.2 Summary Statistics for Dummy Variables (NT = 1,648)

Dummy Variables (0 =No, 1 =Yes)	***Percentage***
Credit access	52.25
If any oxen	80.64
Household head's gender (female)	23.42
Completed primary schooling	40.17
Completed secondary schooling	7.90
Completed tertiary schooling	1.03
Soilconservation	39.87
Waterharvesting	26.58
Irrigation	19.42
Off/non-farm	31.25
Agricultural advisory services	38.29
Remittances	18.51
Midland AEZ	45.87
Highland AEZ	31.55
Lowland AEZ	22.57

Source: Author's calculations.

The descriptive results in Table 5.2 show that 40 per cent of the sample farm households adopted soil conserving climate change adaptation technologies and 26.6 per cent were involved in water harvesting activities. Moreover, 19.4 per cent of them used irrigation for farming.

Besides, 19 per cent of the households got remittances from different sources. Combining the four panels, the educational level of the household head also varied over the years with mean schooling of five years. About 57 per cent had not attended any formal education and were hence illiterate of which 41.3 per centhad not attained any formal schooling, 3.06 per cent had some religious learning and 12.2 per cent had participated in adult literacy programs. About 43.44 per cent of them had attended formal schooling ranging from primary level to tertiary level; out of which 40 per cent had completed primary level (1-8); 7.9 per cent had completed secondary level (9-12); and 1 per cent had done tertiary schooling in which a few had completed university education.

3.2. Econometric Analysis of the Results

3.2.1 The SPF Parameter Estimates

Hypothesis Testing

Before estimating the preferred models, several hypotheses tests were performed on the specified models to evaluate the suitability and significance of the adopted models. We performed two groups of specification tests: tests related to the frontier model and tests associated with the inefficiency effects models.

The related null hypotheses were tested using the generalized likelihood ratio test, which allows an evaluation of a restricted model with respect to the adopted model. The statistic, λ, associated with this test is given by:

$$\lambda = -2\ln\ \pi \ = \ -2\left[\ln\left\{ L(H_0) \Big/ L(H_1) \right\}\right] = -2\left[\ln L(H_0) - \ln L(H_1)\right] \tag{6}$$

where, $L(H_0)$ and $L(H_1)$ are the values of the log-likelihood function under the specifications of the null(H_0) and alternative(H_1) hypotheses respectively. If the null hypothesis is true, then λ has approximately a χ^2 – distribution or mixed χ^2 – distribution with degrees of freedom equal to the number of restrictions assumed to be zero in the null-hypothesis. The results of various null hypotheses tests involving restrictions on the parameters of the adopted models are presented in Table 5.3.

We started by testing the frontier model to choose between CD and TL functional forms. Under this test the assumption that the cereal production in this sample follows the CD functional form (H_0: $\beta_{jh} = \beta_{jt} = 0$, $\forall$j, h and t) was rejected in favor of TL at the 1 per cent level (see Table 5.3). Thus, the result favors TL as our preferred functional form indicating that input and substitution elasticities were not constant among farmers. Another test of the frontier model is for the hypothesis of the existence of technical progress (both zero and Hicks-neutral) technical change. Our test rejected the null hypothesis (H_0) at the 1 per cent level of significance in favor of existence of both types of technical progress.

Other tests were associated with the inefficiency effects models. As presented in Table 3 the tests' results show that the null-hypothesis of no farm-specific factors or no inefficiency effects (H_0) was strongly rejected in favor of the inefficiency effects model at the 1 percent significance level (see Table 5.3). This indicates that inefficiency effects existed for cereal growing famers which in turn imply that the specification of a model that incorporates an inefficiency model is an adequate representation of the data.

Another test on the inefficiency effects model concerns the nature of the inefficiency effects (stochastic or not). If the inefficiency effects are not random, parameters and (H_0: $\gamma = 0$) will be zero because the model will be reduced to a traditional mean-response function. In our case the null-hypothesis was rejected in favor of the stochastic model at the 1 percent significance level (see Table 5.3). This implies that the traditional production function was not an adequate representation of the cereal production data used in this study and it can be said that inefficiencies existed and they were stochastic. The other test determines whether the variables included in the inefficiency effects model had no joint effects on the level of technical inefficiency. The result indicates rejected the null hypothesis confirming that the joint effect of these variables on technical inefficiency was statistically significant.

We also tested the model to see whether it could be reduced to Aigner et al.'s (1977) half-normal specification or truncated-normal distribution (with the null hypotheses H_0: $\mu = 0$). The test result shows that H_0 was rejected at the 1 per cent critical value meaning that truncated-normal distribution was more appropriate than half-normal distribution. Moreover, the other results of the hypothesis tests for inefficiency effects models showed similar results. For example, technical inefficiency was found to be time-varying in both specifications as the null hypothesis of time-invariant inefficiency effects (that is, H_0) was rejected at the 5 per cent level of significance. The test regarding the hypothesis (H_0: $\delta_0 = 0$) where inefficiency effects did not have an intercept was also rejected. Lastly a test was done for evaluating the significance of the weather factors' effects in influencing cereal farming inefficiency. The null hypothesis for this test (H_0: $\delta_k = \delta_{kk} = 0, \forall k$) of no effect of weather factors was rejected and it indicates that inefficiency significantly depended on climate/weather factors for growing cereals in Ethiopia.

Table 5.3 Hypothesis Tests' Statistics for the Adopted Models

Restrictions/Null hypothesis	*Model*	*χ^2–calc.*	*χ^2–tab.*	*d.f.*	*Decision*
Tests associated with the frontier model					
(1) H_0 : $\beta_{jh} = \beta_{jt} = 0, \forall j$, h and t	Cobb–Douglas	390.53	47.67	28	Reject H_o
(2) H_0: $\beta_t = \beta_{tt} = \beta_{jt} = 0, \forall j, t$	No technical progress	154.58	32.09	9	Reject H_o
Tests associated with the inefficiency effects models					
(3) H_0: $\gamma = 0$	No stochastic effects	13.85	5.41	1	Reject H_o
(4) H_0: $\mu = 0$	No truncated-normal	11.96	8.27	1	Reject H_o
(5) H_0: $\delta_0 = 0$	No intercept	6.24	3.59	1	Reject H_o
(6) H_0: $\delta_t = \delta_{tt} = 0, \forall t$	Time-invariant effects	16.62	2.71	2	Reject H_o
(7) H_0: $\gamma = \delta_0 = \delta_m = \delta_k = \lambda_l = 0, \forall m$, k & l	No inefficiency effects	650.94	59.29	30	Reject H_o
(8) H_0: $\delta_0 = \delta_m = \delta_k = \lambda_l = 0, \forall m$, k & l	No joint inefficiency effects	593. 60	53.33	29	Reject H_o
(9) H_0: $\delta_k = \delta_{kk} = 0, \forall k$	No weather factors effects	41.55	21.58	8	Reject H_o

Source: Author's computations.

The data was also checked for statistical diagnostic tests on the SPF model before conducting the estimation. It used the variance inflation factor (VIF) to test the existence of multicollinearity in the hypothesized independent variables. The result reveals that there was no serious multicollinearity problem. We also investigated the correlation between cereal output and the explanatory variables. The result shows that the pairs had low correlation coefficients with each other, with no pairs having a value higher than 0.50 supporting the non-existence of the multicollinearity problem. The correlation result shows that cereal production was positively and highly correlated with production inputs, X_{it}, while it was negatively correlated with most of the weather variables, W_{it}. Moreover, the results show the existence of considerably non-zero correlation coefficients between production inputs and weather factors. Further, as reflected in the descriptive results the weather variables were asymmetrically distributed with statistically significant negative skewness. This is worthy of a separate investigation to underline the potential omitted variables' bias plaguing studies that omit weather variables. Finally, we performed the Hausman test (Wooldridge, 2002) to see if the unobserved fixed effects were best treated as fixed or random effects. The result revealed that the individual effects and explanatory variables were correlated and thereby fixed-effects provided a consistent estimation as compared to random-effects. Accordingly, we estimated robust standard errors fixed-effects estimations. Further, we used the robust standard errors to diminish the heteroscedasticity problem.

SPF Parameter Estimates

We estimated SPF models' parameters, relying on a translog functional form with time trend and separate linear and quadratic climate responses. Prior to taking the logs we normalized the x-variables (divided by their means). Consequently, the first-order coefficients in the model can be interpreted as elasticities of output evaluated at the mean of the data. Parameter estimates of SPF arising from an estimation of the alternative specifications using the TL-GTFE model are reported in Table 5.4. The goodness of fit measured either by the *R*-squared (0.76) or by the log of the likelihood function, is satisfactory in the models indicating that the proposed model is a good representation of the data-generation process. Moreover, the γ parameter associated with variances in SPF, the signal-to-noise ratio, is estimated to be positive and significant in both the models revealing the importance of inefficiency in production variability. The results indicate that inefficiency effects did make a significant contribution to the level and variations in cereal production in the study area. Hence, differences in technical efficiency among farms are relevant for explaining output variability in cereal growing farmers (at least one-third of the variability on the whole).

As shown in Table 5.4, most of the parameter estimates of the models were significantly different from zero at the 5 per cent level or lower. Moreover, the estimated parameters satisfied all production economic theory regularity conditions (that is, positive and diminishing marginal products) which require that the estimated first-order parameters be non-negative and less than one, whereas the bordered Hessian matrix of the first and second-order partial derivatives was negative semi-definite and so they are valid at the point of approximation. Estimates of the first-order parameters indicate that output was statistically significant with respect to labor, machinery and farm size usage in both models' specifications. Hence, an increase in the use of these inputs enhanced cereal production. This is consistent with observations of this cereal farming system as land and labor are both important determinants of output. Few inputs showed their substitutability as seen by their statistically significant negative second-order effects.

Table 5.4 MLEs of the Parameters from the Translog Production Frontier (NT = 1,648)

		With weather factors		Without weather factors	
Variables	*Parameter*	*Estimate*	*Rob. Std. Err.*	*Estimate*	*Rob. Std. Err.*
Constant	β_0	-11.265^{***}	39.163	5.002^{***}	0.419
Fertilizers	β_{x1}	0.033	0.050	0.024	0.050
Agro-chemicals	β_{x2}	0.018	0.030	0.020	0.030
Labor	β_{x3}	0.307^{**}	0.119	0.369^{***}	0.119
Machinery	β_{x4}	0.268^{***}	0.067	0.280^{***}	0.065
Livestock	β_{x5}	0.070	0.070	0.057	0.070
Oxen	β_{x6}	0.107	0.121	0.109	0.122
Area	β_{x7}	0.463^{**}	0.181	0.456^{**}	0.180
Fertilizer*Fertilizer	β_{x11}	-0.003	0.010	-0.002	0.010
Agro-chemicals*Agro-chemicals	β_{x22}	0.005	0.007	0.005	0.007
Labor*Labor	β_{x33}	-0.017	0.023	-0.027	0.023
Machinery*Machinery	β_{x44}	0.062^{***}	0.013	0.059^{***}	0.013
Livestock*Livestock	β_{x55}	0.024^{**}	0.010	0.025^{**}	0.010
Oxen*Oxen	β_{x66}	0.081^{*}	0.046	0.084^{**}	0.046
Area*Area	β_{x77}	-0.077	0.069	-0.066	0.069
Fertilizer*Agro-chemicals	β_{x12}	0.000	0.002	0.001	0.002
Fertilizer*Labor	β_{x13}	0.004	0.008	0.006	0.008
Fertilizer*Machinery	β_{x14}	-0.001	0.004	-0.002	0.004
Fertilizer*Livestock	β_{x15}	-0.011^{**}	0.004	-0.010^{**}	0.004
Fertilizer*Oxen	β_{x16}	0.017^{***}	0.009	0.016^{**}	0.009
Fertilizer*Area	β_{x17}	0.025^{***}	0.013	0.020^{*}	0.013
Agro-chemicals*Labor	β_{x23}	0.003	0.005	0.001	0.005
Agro-chemicals*Machinery	β_{x24}	-0.005^{*}	0.003	-0.006^{*}	0.003
Agro-chemicals*Livestock	β_{x25}	0.009^{**}	0.004	0.008^{**}	0.004
Agro-chemicals*Oxen	β_{x26}	-0.021^{***}	0.006	-0.020^{***}	0.006
Agro-chemicals*Area	β_{x27}	0.005	0.009	0.001	0.009
Labor*Machinery	β_{x34}	0.032^{***}	0.008	0.032^{***}	0.008
Labor*Livestock	β_{x35}	0.013	0.011	0.014	0.011
Labor*Oxen	β_{x36}	-0.019	0.020	-0.020	0.020
Labor*Area	β_{x37}	-0.042	0.030	-0.045	0.029
Machinery*Livestock	β_{x45}	0.002	0.006	0.002	0.006
Machinery*Oxen	β_{x46}	-0.002	0.011	-0.004	0.011
Machinery*Area	β_{x47}	-0.015	0.016	-0.009	0.016
Livestock*Oxen	β_{x56}	-0.012	0.013	-0.012	0.013
Livestock*Area	β_{x57}	0.002	0.018	0.002	0.018
Oxen*Area	β_{x67}	0.020	0.035	0.010	0.035
Time*Fertilizer	β_{x1t}	-0.012	0.010	-0.013	0.010
Time*Agro-chemicals	β_{x2t}	-0.007	0.006	-0.003	0.006
Time*Lobar	β_{x3t}	-0.126^{***}	0.022	-0.130^{***}	0.021
Time*Machinery	β_{x4t}	-0.027	0.016	-0.016	0.015
Time*Livestock	β_{x5t}	-0.001	0.013	0.002	0.013
Time*Oxen	β_{x6t}	0.017	0.023	0.020	0.022
Time*Area	β_{x7t}	0.089^{***}	0.032	0.092^{***}	0.032
Time(1=1999,…,4=2015)	β_t	0.245^{**}	0.187	0.498^{***}	0.164

Time*Time	β_{tt}	0.505^{**}	0.060	0.418^{***}	0.053
Weather factors					
PRECIP	β_{r}	8.990^{***}	3.164		
ATEM	β_{T}	67.214^{**}	25.998		
PRECIP*PRECIP	β_{rr}	-2.055^{***}	0.741		
ATEM*ATEM	β_{TT}	-23.176^{**}	8.830		
	Within	0.764		0.761	
R - squared	Overall	0.660		0.704	
Sigma_u	σ_u	0.613		0.524	
Sigma_v	σ_v	0.741		0.744	
Gamma	Γ	0.406		0.332	

Notes: *: $p<0.05$; **: $p<0.01$; ***: $p<0.001$.

Estimates of the trend and its squared term (which reflects a shift in production technology) were significantly positive at the 5 per cent or lower level meaning that technology shifted outwards (technical progress). As a result, the cereal farmers experienced technical changes (TC) at an increasing rate over time, with an average estimated annual TC rate of 1.16 per cent with a 0.38 per cent dispersion. Regarding technological biases the estimates of time interactions with labor and with farm-size are also significantly negative and positive respectively (Table 5.4). This implies that there was labor-using and farm size-saving technical progress for cereal farmers over the period. Estimates of time interaction with other inputs were not significant implying technical neutrality with respect to these inputs.

Estimates of output elasticities evaluated at the mean of relevant data points show that the elasticities with respect to all inputs were positive, indicating positive marginal products of inputs. This indicates that each input contributed significantly to cereal production though the magnitude differed across inputs. The sum of these input elasticities (returns to scale, RTS) was greater than one meaning that cereal production was characterized by increasing returns to scale, having an average parameter of 1.220 with 38.4 per cent dispersion.

The empirical findings show that climatic/weather conditions clearly affected the production of cereal farming in the study area which was statistically significantly higher. The findings of the model with the weather variables show that weather variables had a positive impact on cereal production as linear parameters of the weather factors show a positive significant relation to cereal production. However, the coefficients of their quadratic terms were negatively significant, implying that the weather variables had a non-linear effect on cereal production. This suggests that climatic/weather conditions were favorable for cereal farming while extreme conditions could induce a significant impact on cereal production. Similar results are reported in previous studies in SSA (Mukherjee et al. 2013; Ogada et al., 2014; Sherlund et al., 2002).

Further, the estimated marginal effects/elasticities of weather variables, which is, the percentage change in cereal production; shows that precipitation affected the percentage change to output by 0.028 percent and temperature by about 1.65 per cent. That is, any increase in average annual precipitation by 1mm will increase cereal production by 0.028 percent and a 1°C increase in annual temperatures could lead to an increase in cereal production by 1.65 per cent. However, interpreting the precipitation results where there is a declining trend of average rainfall in the study area, the results show that a decrease in precipitation by 1 mm annually will lead to a decrease in cereal production by 0.028 percent. The percentage change in cereal production due to the k^{th} weather variable (w_k) evaluated at the mean value of the variable following Lee et al., (2012) and employed in Berisso (2017) is given by:

$$(7) \qquad \frac{\partial \ln y}{\partial \ln w_k} = \left(\beta_{1k} + \beta_{2k} E(w_k)\right) * E(w_k)$$

where, β_{1k} and β_{2k} are the estimated coefficients of linear and quadratic terms respectively and $E(w_k)$ are mean values of the corresponding weather variables. In general, the results show that the combined effect of the weather variables considered had a favorable influence on cereal production over time in the study area.

3.2.2 Technical Efficiency Estimates

The distribution of efficiency scores generated from the full specification (specification with weather factors) and the short specification (specification without weather factors) is presented in Table 5.5. OTE is generated as a product of persistent and transient efficiency components under both specifications. The TTE component generated from the specification with (without) weather factors is found to be quite similar with the mean being 72.0 (71.2) per cent respectively. On the other hand, the opposite is true for the PTE component, which is found to be about 63.0 (80.0) per cent for both specifications respectively. As for the estimated OTE (which is time-variant), the result shows an average of about 45.0 (57.0) per cent from the specifications with (without) weather factors respectively.

Moreover, the variability between persistent and transient efficiency scores clearly demonstrates the existence of significant unobserved farm heterogeneity in the sample and should be considered in efficiency modeling and specifications. Thus the true measure of efficiency, that is, overall technical efficiency; lies somewhere between these extremes, a reason for considering a recently developed more flexible efficiency model --the GTFE model. Further, a comparison of the descriptive statistics (mean and median) of the technical efficiency scores for the models reveals that average technical (in) efficiency differed in model specifications. Inefficiencies under specifications with weather variables were higher compared to models without the weather variables. This provides empirical support for the hypothesis that omission of weather factors could lead to a substantial downward (upward) bias in technical inefficiency (efficiency) estimates. The finding is in agreement with Sherlund et al., (2002) who concluded that the omission of environmental production conditions (weather factors in our case) can result in a marked downward (upward) bias in technical inefficiency (efficiency) estimates.

This result is also in line with Simar and Wilson's (2007) result who introduced a separability condition and argued that efficiency factors (what they called environmental variables) did not influence the frontier but can influence the efficiency scores of units. Banker and Natarajan

(2008) also argue that when correlated inefficiency factors (which they refer to as contextual variables) are ignored in the first-stage estimation (whether it is done using parametric or non-parametric methods) it leads to biased estimates of productivity and hence to productive efficiency estimates.

Table 5.5 Summary Statistics of the Estimated Technical (In) Efficiencies (NT = 1,648)

Percentiles	**With weather factors**			**Without weather factors**		
	RTE	PTE	OTE	RTE	PTE	OTE
1%	0.301	0.235	0.132	0.297	0.670	0.233
5%	0.507	0.351	0.216	0.501	0.713	0.393
10%	0.583	0.387	0.266	0.565	0.731	0.443
25%	0.676	0.514	0.356	0.664	0.766	0.522
50%	0.743	0.667	0.469	0.738	0.808	0.587
75%	0.792	0.748	0.553	0.788	0.838	0.636
90%	0.829	0.797	0.619	0.826	0.855	0.674
95%	0.846	0.851	0.659	0.844	0.868	0.694
99%	0.877	0.881	0.726	0.875	0.893	0.742
Mean	0.719	0.630	0.454	0.712	0.800	0.570
Std. Dev.	0.109	0.159	0.136	0.112	0.050	0.098
Min	0.056	0.168	0.022	0.049	0.559	0.034
max	0.932	0.931	0.798	0.930	0.918	0.804
Yearly mean technical efficiency scores						
1999	0.747	0.624	0.467	0.733	0.799	0.587
2004	0.671	0.656	0.443	0.676	0.804	0.544
2009	0.738	0.624	0.461	0.726	0.799	0.580
2015	0.708	0.624	0.444	0.703	0.799	0.562

Source: Author’s computations.

The lower part of Table 5.5 shows yearly distribution of mean technical efficiency scores. The mean of OTE estimates with (without) weather variables scores were 47(59) per cent in 1999; 44(54) per cent in 2004; 46(58) per cent in 2009; and 44(56) per cent in 2015. The overall implication of the results of the analyses of farmers’ (in) efficiency levels indicates that Ethiopia’s smallholder cereal farmers in the study area were highly inefficient and there was a lot of room for improvement. For instance, the OTE scores imply that farmers will be able to increase their output by about 55(43) per cent with (without) weather factors respectively. Hence, cereal farmers could use their disposable resources more effectively (at the present of technology stage) in general. Further, OTE estimates in particular with (without) weather factors, show that the 1999 output could still have been produced even if the inputs were reduced by 52(41) per cent respectively. A similar interpretation is valid for the other years also.

3.2.3. Results of Technical Inefficiency Effects Models

Empirical findings on the sources of technical (in) efficiency differences among farms are presented in Tables 5.6 and 5.7. We ran several regressions using different inefficiency effects specifications for selecting appropriate explanatory variables to best fit the models. The data was also checked for the existence of multicollinearity in the hypothesized explanatory variables and the results confirmed that there was no multicollinearity problem.

The parameter estimates and their marginal effects from the one-stage MLE method are presented in Table 5.6 and the results of a second-stage regression are presented in Table 5.7. In all the results, a positive sign indicates that the variable increased inefficiency, that is, a parameter estimate with a negative sign shows that the parameter had a positive effect on technical efficiency. Note that in MLEs instead of interpreting the magnitude of the coefficients of the variables in the inefficiency function, we use them in computing marginal effects. Thus, we interpret the magnitude of the marginal effects for MLE results and the magnitude of the coefficients for the second-stage regressions as they are the same as marginal effects in the latter case. The empirical results of all inefficiency effects models show that most of the specified farmer-specific characteristics, adaptation strategies, agro-ecological and climatic factors explaining the inefficiency effects had a significant effect in determining cereal farming technical (in) efficiencies.

Determinants of Persistent Technical (In) efficiency

The empirical MLE results show that the coefficients of time-invariant and location-specific factors (midland and highland AEZs, and altitude) in the specification with weather factors related negatively and significantly to persistent inefficiency (Table 5.6). This shows that these variables had a significant positive effect on the persistent technical efficiency level, which means that a one unit increase in these variables could ceteris paribus raise the PTE level by the same unit. On the other hand, the opposite is true for the specifications without weather factors for the effect of these variables (except for altitude) on persistent technical (in) efficiency which is inconsistent with previous similar studies.

Determinants of Transient Technical (In) efficiency

Similarly, MLE's empirical results on transient technical inefficiency effects (Table 5.6) show that transient inefficiency was positively and significantly affected by the age of the household head, secondary schooling level and extreme temperature variations under both (full and short) specifications. This implies that an increase in each variable reduced TTE. However, transient inefficiency was negatively and significantly related to the gender of the household head, household size and the number of plots under the full specification. It was negatively and significantly related to remittances, annual average rainfall and average extreme temperature levels under the short specification. Hence, an increase in these factors, ceteris paribus, led to an increase in TTE during the period.

Table 5.6 MLEs of Determinants of Persistent and Transient Technical Efficiency (NT = 1,648)

Variables	***Determinants of transient technical (in)efficiency (TTE)_MLE***					
	With weather factors			*Without weather factors*		
σ_u : (Time-variant)	Coef.	Std. Err.	Mean MEs	Coef.	Std. Err.	Mean MEs
Farm-specific factors						
Household head's gender	-0.315*	0.186	-0.059	-0.314*	0.18	-0.061
Household head's age	0.080**	0.033	0.015	0.075**	0.031	0.015
Household head's age sq.	-0.064**	0.03	-0.012	-0.061**	0.029	-0.012
Household size	-0.060*	0.035	-0.011	-0.052*	0.033	-0.010
Primary educ.	-0.003	0.167	-0.001	-0.006	0.162	-0.001
Secondary educ.	0.485*	0.289	0.092	0.485*	0.282	0.095
Tertiary educ.	0.456	0.702	0.086	0.396	0.7	0.077
If any ox	-0.249	0.185	-0.047	-0.234	0.181	-0.046
Farm size	-0.012	0.035	-0.002	-0.015	0.033	-0.003
Credit use	0.047	0.155	0.009	0.056	0.149	0.011
Population pressure	0.09	0.104	0.017	0.089	0.097	0.017
Remitances	-0.277	0.218	-0.052	-0.387*	0.222	-0.075
Adoption technologies						
Number of plots	-0.115**	0.059	-0.022	-0.097*	0.054	-0.019
Soil conservation	-0.191	0.169	-0.036	-0.205	0.166	-0.04
Water harvesting	-0.175	0.191	-0.033	-0.273	0.189	-0.053
Irrigation	-0.113	0.221	-0.021	-0.213	0.219	-0.042
Off/non-farm activities	0.149	0.17	0.028	0.113	0.165	0.022
Agri. Ext. services	-0.246	0.165	-0.046	-0.237	0.159	-0.046
Weather factors						
PRECIP	-0.03	0.031	-0.006	-0.076**	0.03	-0.015
ATEM	-1.256	0.869	-0.237	-1.806**	0.843	-0.352
PRECIP sq.	0.733	0.538	0.062	0.001**	0.001	0.001
ATEM sq.	0.073	0.051	0.014	0.106	0.049	0.021
Rainfall variation	3.374	68.18	0.637	-59.151	67.514	-11.54
Rainfall variation sq.	-14.072	38.052	-2.656	21.263	37.455	4.148
Temperature variation	0.318**	0.115	0.06	0.323***	0.113	0.063
Temperature variation sq.	-0.021*	0.013	-0.004	-0.023*	0.013	-0.004
Time	0.056	0.545	0.011	0.303	0.528	0.059
Time sq.	-0.05	0.208	-0.009	-0.155	0.202	-0.03
Constant	8.445	6.594		15.259**	6.468	
σ_v: (Time-variant)						
Constant	-1.282***	0.069		-1.287***	0.068	
log likelihood	-1504.467			-1512.154		
	Determinants of persistent technical (in)efficiency (PTE)_MLE					
	With weather factors			Without weather factors		
σ_u: (Time-invariant)						
Constant	-0.824***	0.081		-2.413***	0.74	
σ_v: (Time-invariant)	Coef.	Std. Err.	Mean MEs	Coef.	Std. Err.	Mean MEs

Midland AEZ	-2.178***	0.321	-0.047	1.097***	0.217	0.127
Highland AEZ	-0.305	0.475	-0.221	3.037***	0.444	0.145
Altitude	-0.047***	0.005	-0.001	-0.003***	0.005	-0.001
Mkt proximity	-0.002	0.011	-0.013	0.001	0.008	0.014
Constant	-2.351***	0.468		2.175***	0.404	
Log likelihood	-1416.481			-1175.201		

Notes: *: $p<0.05$; **: $p<0.01$; ***: $p<0.001$.

Interpreting the magnitude of the marginal effects of the MLE results, we find that the marginal effect of household head's gender (female) on the transient technical inefficiency function was negative for both specifications, the mean being about 0.060. Thus, on average, transient technical inefficiency reduced by 0.6 per cent for a 10-point increase in the household head's gender. Similarly, an increase in the share of household size and number of plots by one percentage point, on average, reduced transient inefficiency by 0.011 and 0.022 per cent respectively. A one unit increase in remittances reduced transient inefficiency by 0.075 per cent. On the other hand, a 1 percent increases in the age of the household head and secondary educational level, on average, increased transient inefficiency by 0.015 and 0.001 per cent respectively. A similar interpretation is valid for the other variables for each (in) efficiency component.

Determinants of Overall Technical (In) efficiency

The next concern related to estimates of technical inefficiency effects on OTE. We used the two-stage approach to explain factors that can affect OTE applying panel regression methods. For comparison, a POLS model and panel models with (respectively) fixed and random effects were also run with the efficiency score (treated as a continuous dependent variable with no limits) as the dependent variable. Results from the three OLS estimates were also compared with MLE estimates, after running the two-limit Tobit random effects model using censored efficiency values below by zero and above by one as the dependent variable. The conclusions (estimates) from OLS particularly those from random-effects are the same as those derived from the MLE/Tobit model due to the reasons discussed in the methodology section. We used the robust (clustered) standard errors in all OLS estimations to diminish the heteroscedasticity problem. More importantly, the usual standard errors of the POLS estimator are incorrect and tests based on them are not valid. Correct standard errors can be estimated with the so-called cluster-robust covariance estimator treating each individual as a cluster. For each specification we tested the suitability of POLS and RE models, using the BP/CW F-test. The test results reveal that POLS and RE were the same and both were efficient under the short specification while the RE model was better than a pooled effects model under the full specification. Similarly, for comparing the RE model with the FEM we used the Hausman test and the test results favored the FE model.

However, when the time dimension of the panel is short, most of the variations in the dependent and independent variables are across units and so the fixed effects approach can introduce problems of multicollinearity and reduce the precision of the estimates. Belotti et al., (2012) suggest that the fixed effects approach is feasible when the length of the panel is at least 10 years. Our semi-unbalanced dataset contained farms whose age varied from 3 to 4 years and so we preferred the REs model. Accordingly, the interpretation reported is primarily based on the results from random-effects estimations, unless otherwise stated. The parameter estimates of all models (POLS, RE, FE and Tobit regressions) are presented in Table 5.7.

The empirical results show that overall technical inefficiency (Table 5.7) was negatively and significantly related to total farm size, gender of household head, household size, remittances, market proximity centers, climate change related adoption technologies (number of plots, soil conservation, participation in agricultural advisory services and water harvesting technologies), linear terms of weather factors and agro-ecological variables. Hence, an increase in these factors reduced the overall technical inefficiency and a declining trend in overall inefficiency ceteris paribus was observed during the period of our study which means that OTE increased with an increase in these variables.

Table 5.7 Estimates of Determinants of the Overall Technical (In)efficiency (NT = 1,648)

Variables	**With weather factors** (†Rob.std. error)				**Without weather factors**(†Rob.std. error)			
	OLS			***MLE***	***OLS***			***MLE***
	POLS	***RE***	***FE***	***RE-Tobit***	***POLS***	***RE***	***FE***	***RE-Tobit***
	1.517	1.021	1.436	1.002	6.202***	6.202***	3.829***	6.202***
Constant	1.186	1.071	0.943	1.147	1.443	1.443	1.297	1.534
Farm-specific factors								
	-0.026*	-0.052***	-0.062***	-0.053***	-0.050***	-0.050***	-0.099***	-0.050***
Household head’s gender	0.015	0.011	0.013	0.01	0.011	0.011	0.018	0.01
	0.010***	0.010***	0.010***	0.010***	0.014***	0.014***	0.015***	0.014***
Household head’s age	0.002	0.001	0.001	0.001	0.002	0.002	0.002	0.002
	-0.008***	-0.008***	-0.008***	-0.008***	-0.011***	-0.011***	-0.012***	-0.011***
Household head’s age sq.	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.001
	-0.009***	-0.009***	-0.008***	-0.009***	-0.010***	-0.010***	-0.011***	-0.010***
Household size	0.002	0.002	0.002	0.001	0.002	0.002	0.003	0.002
	-0.02	-0.001	-0.008	-0.001	-0.007	-0.001	-0.02	-0.01
Primary educ.	0.013	0.009	0.009	0.008	0.01	0.001	0.014	0.01
	-0.01	0.051**	0.078***	0.053***	0.073***	0.073***	0.113***	0.073***
Secondary educ.	0.025	0.019	0.021	0.016	0.016	0.016	0.027	0.017
	0.106**	0.06	0.133**	0.065*	0.039	0.04	0.140***	0.04
Tertiary educ.	0.044	0.042	0.047	0.038	0.036	0.036	0.042	0.041
	-0.02	-0.004	-0.003	-0.003	-0.028**	-0.028**	-0.02	-0.028**
If any ox	0.017	0.01	0.01	0.01	0.012	0.012	0.016	0.011
	-0.006***	-0.003**	-0.002**	-0.003**	-0.005***	-0.005***	-0.004**	-0.005***
Farm size	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.001
	0.004	0.01	0.014**	0.01	0.013*	0.013*	0.020**	0.001
Credit use	0.009	0.007	0.007	0.007	0.008	0.008	0.001	0.009
	0.005	0.01	0.011*	0.010*	0.009	0.01	0.01	0.01
Population pressure	0.008	0.006	0.006	0.005	0.008	0.008	0.011	0.006
	-0.027**	-0.037***	-0.041***	-0.038***	-0.056***	-0.056***	-0.074***	-0.056***
Remitances	0.014	0.01	0.01	0.01	0.012	0.012	0.014	0.012
	0.001	-0.003*		-0.003*	0.001	0.001		0.001
Mkt proximity	0.001	0.002		0.002	0.001	0.001		0.001
Adoption technologies								
Number of plots	-0.010***	-0.012***	-0.012***	-0.012***	-0.016***	-0.016***	-0.017***	-0.016***

	0.003	0.002	0.002	0.002	0.002	0.002	0.003	0.003
	-0.037***	-0.031***	-0.029***	-0.031***	-0.045***	-0.045***	-0.041***	-0.045***
Soil conservation	0.011	0.008	0.008	0.008	0.01	0.01	0.012	0.01
	-0.026**	-0.021**	-0.023**	-0.021**	-0.059***	-0.059***	-0.046***	-0.059***
Water harvesting	0.012	0.009	0.009	0.009	0.011	0.011	0.013	0.011
	-0.001	-0.001	-0.001	-0.001	-0.029**	-0.029**	-0.01	-0.029**
Irrigation	0.013	0.012	0.013	0.011	0.014	0.014	0.019	0.014
	0.038***	0.033***	0.026**	0.033***	0.030**	0.030**	0.032**	0.030***
Off/non-farm activities	0.012	0.009	0.01	0.008	0.011	0.011	0.014	0.01
	-0.021*	-0.033***	-0.036***	-0.033***	-0.055***	-0.055***	-0.059***	-0.055***
Agri. Ext. services	0.012	0.008	0.008	0.008	0.009	0.009	0.013	0.009
Agro-eco-climatic factors								
	-0.009***	-0.008***	-0.003**	-0.008***	-0.018***	-0.018***	-0.021***	-0.018***
PRECIP	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002
	-0.318***	-0.261**	-0.280**	-0.259**	-0.717***	-0.717***	-0.516***	-0.717***
ATEM	0.107	0.096	0.099	0.104	0.132	0.132	0.138	0.138
	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
PRECIPsq.	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	0.019***	0.016***	0.017***	0.016***	0.040***	0.040***	0.031***	0.040***
ATEM sq.	0.006	0.005	0.005	0.005	0.007	0.007	0.007	0.007
	32.553***	23.955***	8.173**	23.404***	2.23	2.23	-1.93	2.23
Rainfall Variation	4.083	3.441	4.069	3.991	3.742	3.742	5.65	4.555
	-167.35**	-137.89***	-73.89***	-135.89**	-34.89*	-34.89*	0.001	-34..991
Rainfall Variation sq.	19.00	17.62	20.12	20.34	19.58	19.58	0.001	25.63
	0.040***	0.044***	0.056***	0.045***	0.060***	0.060***	0.065***	0.060***
Temperature Variation	0.007	0.007	0.007	0.006	0.009	0.009	0.011	0.007
	-0.002**	-0.002***	-0.004***	-0.002***	-0.004***	-0.004***	-0.003**	-0.004***
Temperature Variation sq.	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	-0.198***	-0.232***		-0.233***	0.063	0.06		0.06
Midland AEZ	0.063	0.062		0.062	0.066	0.066		0.067
	-0.278***	-0.359***		-0.361***	0.081	0.08		0.08
Highland AEZ	0.085	0.086		0.091	0.085	0.085		0.089
	0.0002	0.0002*		0.0002*	-0.0003*	-0.0001*		-0.0003*
Altitude	0.0001	0.0001		0.0001	0.0002	0.0001		0.0002
	-0.03	-0.028	-0.007	-0.028	0.068**	0.068**	0.011	0.068**
Time trend	0.027	0.021	0.024	0.024	0.027	0.027	0.035	0.031
	0.003	0.002	-0.005	0.002	-0.033***	-0.033***	-0.02	-0.033**
Time trend sq.	0.01	0.008	0.009	0.009	0.01	0.01	0.013	0.012
R-squared	0.472	0.308	0.324		0.417	0.32	0.338	
Log likelihood				747.5				632.3
Sigma_u		0.139	0.201	0.146***		0.001	0.145	0.001
Sigma_e		0.12	0.12	0.119***		0.173	0.173	0.165
Rho		0.573	0.738	0.599***		0.001	0.413	0.001

Note: *****: $p<0.05$; ******: $p<0.01$; *******: $p<0.001$; and ☨: the rubout std. errors displayed for each explanatory variable in the lower-cells of the sub-table.

However, overall technical inefficiency was positively significantly related to farmers' credit use, household head's age, secondary educational levels, participation in off/non-farm activities, altitude, population pressure and linear terms of average extreme variations in weather variables from their optimal mean level. Hence, an increase in these factors reduced OTE ceteris paribus during the study period.

Effects of Household head's characteristics on farm productive (in) efficiency:

Gender: For this study being a female household head shows negative and significant effect on technical inefficiency showing that female-headed households are more efficient than their male counterparts. The result may be explained, due to the fact that the farmers are highly characterized by smallholder farmers who are farming on very small farm land, with female farmers cultivating on an average of less than one and half hectares and that may not require laborious efforts. Another possible reason may be since this performance is short term farming performance (the transient (in) efficiency which is varying yearly). On the other hand, the result may imply something that is inherent in the family system of rural Ethiopia. Females become head of a household only when males are deceased or not around, therefore when females are head of the household they take on all households leading responsibility including farming without any alternative dependence. This may have subjected them to be more commitment in attending meetings organized by agricultural extension officers, exhibited by females compared to their male counterparts.

Age: Head's is found to have a positive and significant effect on cereal farming inefficiency in this study, while its square showed positive effect, indicating a non-linear relationship of age with technical efficiency. The negative sign indicates that older household heads are less productive as compared to younger ones, supports the argument that farmers become less efficient as they get older. Moreover, the result can be explained in terms of crop production practices. The negative sign for the coefficient could be attributed to the unwillingness of older and more experienced to use new techniques and modern inputs. Whereas younger farmers, by their greater opportunities modernization, tend to be more open, may be more skillful in their search for information and likely to be exposed to the application of new methods and better techniques. This, in return, will improve their level of technical efficiency. This result may be supported by the result from the descriptive summary, as the age of the farmers ranged 17 to 103 years with an average of 51 years, implying that farmers under this study were relatively old; a condition that might have affected overall efficiency negatively, as cereal farming is labor intensive. On the hand, the positive effect of the age-square further indicates that older farmers are more efficient as compared to younger ones. The explanation is that older farmers generally gain experience in cereal production and grow the cereal more efficiently. In general, these two contrasting effects might have neutralized each other. Older and more experienced farmers have more knowledge on their land and traditional practices, but are less responsive to take new ideas. However, considering the possible tradeoffs between the two contrasting effects, literature accounts for the possibility of mixed results: negative in the study of (Wadud and White, 2000), but positive in the study of (Haji, 2006).

Schooling: Farmer's education is a factor that the literature frequently relates to farming efficiency, despite the empirical evidence reveals mixed results the literature. Several studies found positive effect of education on efficiency (Bamlaku *et al*., 2009) arguing that education is associated with efficient management of production systems and hence higher farming efficiency levels. In contrast (Bravo-Ureta and Evenson, 1994 among others) argued that when a farmer gets access to better education, he or she may get better opportunities outside the farm sector to pursue other income earning activities, hence resulted in negative effect to farming efficiency. Differently, few authors (see Temesgen and Ayalneh, 2005) argued that in developing countries education do not has clear effect on performance of the agricultural. They claim that education may not be important (relevant) to agricultural productivity which is mainly traditional not equipped with modern technology rather based on a common practice.

Aiming this, current study hypothesized educational levels may matter than making dummy, hence specified farmer's formal schooling in educational levels, particularly primary, secondary and tertiary educational levels of the HH head to see the effect of schooling levels on technical inefficiency. As anticipated, the result reveals mixed results. The secondary and tertiary level schooling of the head showed positive significant effect on farming inefficiency. In contrast, technical inefficiency appears to be decreasing in the primary level schooling. This shows that inefficiency is lower for less educated or unschooled HH head, making them to be more efficient in cereal production. The positive significant relation of secondary and tertiary educational levels to the inefficiency indicates that these levels of farmer's education have negative effect on farming efficiency. In particular, it shows that higher levels formal education has adverse effect on farming efficiency. This likely reflects that farming might be seen a secondary occupation for those with higher level of schooling, who could focus primarily on superior income source availability, based on their education and/or skills. Thus, for higher educated ones, farming gets relatively less of their attention and thus exhibits greater technical inefficiency. The result is in line with other similar studies (Sherlund *et al.,* 2002 and Ogada *et al.,* 2014) who argued, education to increase the likelihood of non-farm employments as some level of education gives the skill to create and better manage some small businesses.

Effects of the Farm/Household's characteristics on farm productive (in) efficiency:

Family size: Crop farming is labor-intensive activity in Ethiopia. Accordingly, availability of farm labor within the HH showed significant effect on cereal productive efficiency as HH's family size has showed negative and significant effect on inefficiency level. The result is in line with the literature; (such as Haji, 2006) argued that an increase in the number of members in the family could increase crops production thus productive efficiency. The possible reason may be due to the fact that large household's size enhances the availability of labor which may guarantee increased efficiency. The result confirms the importance of family labor as a critical input in rural farming, specifically, at the peak farming cycle such as land preparation, planting and harvesting time during which the farmer faces the labor bottlenecks. This empirical result also concedes with the significant contribution of labor input (which is mostly originated from HH's members) to enhance cereal production. Thus ceteris paribus, the corresponding magnitude shows that an increase in HH size could lead to a rise in efficiency by 0.9 per cent.

Farm size: For this research total farm size is created by multiplying the number of plots that farmers cultivate with the size of cultivated land also as an interaction variable is included in the analysis to assess the effect of farm size on farming efficiency of dissected plots for a given size of cultivated land. However, a number of studies show controversial results about the relationship between farming efficiency and farm size. Yet, in this study, an empirical finding shows that farm size is negatively significantly affects farming inefficiency. The sign of coefficient on this parameter implies that cultivating large farm size reduces inefficiency. It may also represent the reduced risk that different plots provide if the plots are located sufficiently disbursed, such that farmers face different degrees of weather-induced variation and mineral content on the different plots. Further, this empirical finding is in line with the descriptive and the frontier results indicate that improvement of cereal production, hence technical efficiency strongly depends on cereal farms attaining an adequate farm size. The result is in coincides with similar studies in SSA (Sherlund et al., 2002).

Population pressure: this is an interaction variable; the ratio of number of the household member older than 14 years to the cultivated farm size was used in the inefficiency equation to investigate the claim that population pressure or overcrowded agricultural land holdings adversely affect efficiency. Densely populated areas are characterized by high scarcity of farmlands, where farmers may have the incentives for more efficient utilization of inputs than those in areas of relatively lower scarcity. In this study, it is found that population pressure is related passively significantly to technical inefficiency, implying a negative and significant effect on technical efficiency level. This indicates that the larger the household relative to the farm size, the lesser the technical efficiency.

Mkt proximity: Another factor worth considering, as a variable affecting farming efficiency, is proximity to factor markets. It is hypothesized that households located near markets are expected to have higher farming efficiency than those located in remote areas. The assumption is that proximity to markets increases farmers' access to credit facilities and income-generating activities. By contrast, other people argue that access to markets may increase the non-farm employment opportunities with higher returns than from farming, leading them to reallocate labor from farm to non-farm activities, tends to be less efficient. Nevertheless as anticipated, our empirical result revels that proximity to markets reduces technical inefficiency levels significantly, depicting a positive effect on technical efficiency in the study area. This result is explained by the fact that, proximity to market places are more desirable as far as improved technical efficiency is concerned since farmers close to market places have access to better market information and means of transportation. Closeness to market may also offer alternative employment opportunities to absorb excess labor from the farms. Similar results have been noted by (Nyagaka *et al.*, 2010).

Remittance: Results also reveal the strong and important role of remittance in affecting cereal farming inefficiency. The coefficient of this variable showed remittance negatively and significantly associated to cereal productive inefficiency. This indicates that an increment in remittance leads to an increase in efficiency of cereal farming. Hence, households that accessed remittance were associated with higher farming efficiency than those that did not receive remittance at all. This could be most probably, because, the remittance facilities obtained from (national or international sources) allowed the farmers to diverse away from their attentive farming practices, making farm activities less intensive, developed dependence attitude on their sources.

Credit facilities: It is found in this study that, credit access has positive relation with the level of technical inefficiency. This shows that farmers accessed to credit was associated with lower technical efficiency than those that did not seek credit at all. This could be resulted due to the reason that farmers who have better access of credit might not use their money appropriately or might use for non-farm activity. More precisely, those who accessed credit could engage in non-farm activity. Most probably, the credit facilities from (financial or non-financial sources) allowed the households to diversify away from agriculture, making supervision of farm activities less intensive. Moreover, they may not demand credit for agriculture rather for other reasons. Therefore, migration of active work force in the family members to non-farm sector could leave household to be less efficient in farm production. Alternatively, credit directed to agriculture may have eased resource constraints among the farmers, leading to over-application of farm inputs. This may also explain the negative correlation between farm-household's credit assess to technical efficiency.

Effects of adoption technologies on farm productive (in) efficiency:

In the climate change literature modern climate change adaptation strategies are key activities in enhancing crop productivity. This is determined by farmers' decision to plant a given type of crop, type and amount of inputs to use, planting trees, using more number of plots for cultivation, using soil conservation and water harvesting activities, and controlling erosion in degraded lands can greatly improve soil fertility and thus enhance crop production and hence productive efficiency. Most of the climate change adoption technologies specified in the analysis affected technical inefficiency negatively significantly. Consequently these adoption technologies evince a positive impact on cereal farming technical efficiency.

Effect of soil conservation and water harvest: It is well recognized in the climate change literature that investing in soil and water conservation measures is a key adaptation strategy for developing countries and more particularly for SSA countries (Kurukulasuriya and Mendelsohn, 2008). For this study, as can be observed from table 5.7, soil conservation and water harvest have both negatively and significantly influenced technical inefficiency. The negative and significant correlation between technical inefficiency of these technologies implies that investing in soil conservation and water harvests have positive effect on technical efficiency for those farmers who adopted such strategies.

Number of plots: Land fragmentation was represented by the number of plots of land on which the farmer has grown cereal, included in the analysis to assess the effect of dissected plots for a given size of cultivated land on technical efficiency. It was hypothesized that a farmer with more number of plots is more inefficient than a farmer with more consolidated area. The reason might be that fragmented land is difficult for effective management of the crop and hence a farmer having more plots is expected to loss time by moving between plots. However, for this study this variable was negatively associated with cereal farming inefficiency significantly. The result implies that for a given amount of land for cereal cultivation, an increase in the number of plots leads to increased cereal farming technical efficiency. The positive sign on this coefficient may also represent the reduced risk that different plots provide if the plots are sufficiently disbursed, such that farmers face different degrees of weather-induced variations and mineral content on the different plots. Moreover, the result can be explained in terms of access to farm land and that farmers with more plots are likely to adopt innovations because they may be willing and able to bear more risks than their counterparts and may have preferential access to farm inputs and this will enable them to improve the level of their cereal farming technical efficiency.

Agricultural extension service: The coefficient of extension contact in this study is as expected. It was negatively associated with cereal farming inefficiency significantly; suggesting that such a contact result in a positive and significant effect on household level technical efficiency. The explanation is that farmers who have adequate extension contact are expected to have better information about scientific way of farm production so avail themselves of modern agricultural technology for input mobilization, input use and disease control, which enables them to reduce technical inefficiency.

Off/non-farm activities: The result of this study revealed that engagement in off/non-farm activities is found to have significant positive effect on farmers' technical inefficiency. This means that farmers who engaged more in diversified activity end up with considerably less cereal farming technical efficiency compared to those less participated in the diversification. This could be because farmers who engaged in non-farm activity as source of income beside crop production are more likely to be preoccupied with other income generating activities and hence pay less attention to important agricultural practices. Moreover, it can be argued that managerial input may be withdrawn from farming activities with increased participation (particularly more educated) in off/non -farm activities, which leads to diminish in farm technical efficiency. The finding is in line with work of (Bamlaku et al., 2009) found higher inefficiency of production with involvement of farmers in off-farm activities, who argue that increases in non-farm work are accompanied by a relocation of time away from farm-related activities. Nevertheless, it is contrast to the findings of (Beyan et al., 2013); who argue that presumably farmers having greater off-farm income might be more efficient as they gain experience because off-farm income might be a proxy for agricultural credit.

Effects of agro-eco-climatic factors on farm productive (in) efficiency

The estimation results show that most of the weather factors had a significant impact on the overall cereal farming production (in) efficiency. The coefficients of linear and squared terms of the weather variables show that cereal farming productive (in) efficiency was generally sensitive to weather factors. Moreover, the results of the squared terms show that weather factors had significant non-linear effects on cereal productive (in) efficiency. The results indicate that average annual amount of (rainfall and temperature) was significantly negatively related to overall technical inefficiency demonstrating that both were beneficial for cereal farming technical efficiency. However, the results also show that excess temperature or rainfall was detrimental, as there is an inverted U-shaped relationship between weather variables and technical efficiency of cereal farming in the study area.

By contrast, the coefficients of weather variation terms (of precipitation and temperature) showed a significant positive effect on technical inefficiency. This shows that what mattered most was not only the amount of rainfall and temperature but also their variability as represented by the coefficients of variations from mean rainfall and mean temperature which are supposed to be the optimal levels. When rainfall and temperature diverged from their mean values (both upward and downward) the level of productive efficiency significantly diminished. This may be because in case of dry or excess rainfall conditions, fertilizer adoption may burn seeds and increase the probability of crop failure.

The positive significant effect of the average annual rainfall on cereal efficiency could be due to the fact that rainfall enhances crop production as it improves the soil's capacity and enables it to use the fertilizers and other inputs effectively (Tchale and Suaer, 2007) hence enhancing productive efficiency. However, this is up to a point and then production, hence productive efficiency, starts declining as demonstrated by its significant squared terms' coefficients. On the other hand, as can be seen in Table 5.7, a considerable deviation from the optimal mean values as the extreme quantity, that is, its variability, as represented by the coefficients of variations have an unfavorable effect on cereal farming productive efficiency. This shows that an increase from this level will harm productive efficiency, while a decrease will have a benefit. Like annual precipitation, annual mean temperature enhanced cereal productive efficiency significantly but up to an optimal level as demonstrated by its significant parameters of the squared terms. Moreover, the results show that average extreme temperatures, as represented by their coefficients of variation had an unfavorable effect on cereal farming productive efficiency. This shows that an increase from this level will harm productive efficiency, while a decrease will have a benefit. This result coincides with the results of similar studies in SSA (Mukherjee et al., 2013; Ogada et al., 2014; and Sherlund et al., 2002).

Marginal Impact of Weather Variables

The coefficient of quadratic terms of both temperature and precipitation is negatively significant, implying that weather variables had a non-linear effect on cereal productive (in) efficiencies. However, the effect of weather variables on cereal efficiency is not obviously determined simply by looking at the coefficients. This is since both the linear and squared terms play a role. Their effect can be interpreted based on the marginal effects or elasticities of weather variables. Thus, it is important to observe the overall effect of an infinitesimal change in each specified weather variable on efficiency for aggregate interpretations due to squared terms.

Accordingly, the marginal effects on efficiency due to the k^{th} weather variable (w_k) evaluated at the mean value of the variable following Lee et al., (2012) and employed in Berisso (2017) is given by:

(8) $$\frac{\partial \Phi}{\partial w_k} = \left(\delta_{1k} + \delta_{2k} E(w_k)\right) * E(w_k) \quad ;$$

where, Φ is the technical efficiency score, δ_{1k} and δ_{2k} are the estimated coefficients of linear and quadratic terms respectively and E (w_k) are mean values of the corresponding weather variables.

Table 5.8 Calculated Marginal Effects of Weather Variables on Cereal Productive Efficiencies

Weather Variables	*Marginal Effects TTI*	*Marginal Effects OTI*
Annual rainfall (PRECIP)	-1.387	-0.460**
Annual maximumtemperature (ATEM)	-2.628**	-0.895***
Annual rainfall variation	-0.423	-0.094***
Average temperaturevariation	1.394***	0.432***

Note: *****: p<0.05; ******: p<0.01; *******: p<0.001.

One can interpret the effects of increases in temperature by 1°C and increases in precipitation by 1 mm per annum and also their extreme variations on cereal productive efficiency using the result from the marginal effects. The findings show that weather factors had a favorable influence on cereal production and hence on cereal productive efficiency, but had unfavorable effects in their extreme variations. However, despite these results the context or trends of annual weather factors' distribution in the study area, the findings specifically show a negative impact of the precipitation variables on cereal production and cereal productive efficiency while the opposite is true for the temperature variables. Thus, the study confirms that climate variability is one of the critical drivers of cereal production and efficiency in many African agrarian households (the World Bank, 2006).

This essay also considered households located in different AEZs which differ in their location (altitude) and agro-ecological factors (climatic conditions and soil quality) by using variables to account for geo-climatic and location heterogeneities in some efficiency analyses (Karagiannis and Sarris, 2005; and Madau, 2011).Under full specification, altitude influenced technical inefficiency negatively and significantly. Out of the regional dummy variables included in the regression or proxied for climatic conditions, soil types and quality the variables highland and midland AEZs considerably affected cereal productive inefficiency significantly and negatively. Farming in midland and highland areas as compared to lowland areas contributed to an increase in cereal productive efficiency. Therefore, efficient production is likely to be in areas in mid to higher altitudes where rainfall and temperature are favorable for cereal production; similar results were found by (Madau, 2011; Sherlund et al., 2002; and Bamlaku et al., 2009).

Our empirical findings suggest that a declining trend in overall inefficiency ceteris paribus is observed during the period under full specification. Thus, overall inefficiency declined over time, even though the magnitude of the decline was really low (0.028). This indicates a weak effect of time on efficiency levels. Hence, in general the empirical findings show that the frontier shifted upward and inefficiency declined over time during our sample period.

In the analyses of the inefficiency effects models we see that the estimated relationships between the technical inefficiency measures and the correlates are broadly similar across both specifications (specifying with weather factors – full specification and specifying without weather factors – short specification). Nevertheless, when the ‘weather factors’ are excluded, despite most of the inefficiency effects variables being statistically significant only a few result in inconsistent effects in reality than when specified with weather factors. For example, altitude, regional dummy variables and time trend variables were significant under both model specifications. Yet, under the short specification out of the regional dummy variables proxied for soil types and quality, highland and midland AEZs variables considerably affected all types of productive efficiency significantly and negatively; while they had the opposite effect in the full specification. This is counterintuitive and inconsistent with the reality and also the findings of previous studies on Ethiopian crop production. A more precise estimate is obtained when this parameter is generated by the full specification under which the model’s adequacy is exhibited by fitness measures as a robust and more appropriate model. Hence, the inclusion of climate variables (relatedly) improves the precision with which one can explain apparent technical inefficiencies. Therefore, this essay concludes that the omission/inclusion of climate variables not only resulted in biased technical inefficiency estimates, but also significantly affected the estimates of the relationships (precision and significance levels) between technical inefficiency scores and some inefficiency effects variables.

5. Conclusion and Policy Implications

This study estimated persistent and transient technical (in) efficiency and explained inefficiency differentials in both inefficiency components among smallholder cereal farmers in Ethiopia using household-level panel data for 1999–2015. The study used a 4-error component SPF panel data model that includes random noise, time-invariant farm-effects (heterogeneity) along with persistent and transient technical inefficiency. This model was extended to accommodate factors that can explain persistent (PTE) and residual (RTE) or transient components and compute marginal effects of the determinants on each type of inefficiency component. The study employed a mixed efficiency analysis approach in two steps; where first a one-stage approach SFA method was used to estimate PTE and RTE scores simultaneously to explain their differentials. Second, in a two-stage approach it explained the overall inefficiency effects. Here the overall (OTE) efficiency scores were estimated as a product of PTE and RTE from the first stage efficiency estimates and were regressed on the covariates at the second-stage using the panel data estimation method.

The first-step estimates of the parameters from SPF indicated that machinery, cultivated land and farm labor significantly enhanced cereal production. The findings show that weather variables had a positive impact on cereal production. Estimates of production elasticities from both specifications (with and without weather variables) showed that each input contributed significantly to enhancing cereal production. The results further show that cereal farming was technically regressed at an increasing rate and exhibited increasing returns to scale. The estimated efficiency scores show that the transient efficiency component of specifications with (without) weather factors was quite similar with the mean being 72.0 (71.2) per cent respectively. The persistent efficiency component (from time-invariant policy/management effect) from both the specifications was about 63.0 (80.0) per cent, while mean of the overall technical efficiency (which is time-variant) was 45.0 (57.0) per cent respectively.

Estimated efficiency results across different specifications in general illustrate significant variations in efficiency estimates across the different specifications showing that efficiency estimations were sensitive to a model's specifications. Moreover, variability between persistent and transient efficiency scores clearly demonstrates the existence of significant unobserved farm heterogeneity in the sample and should be considered in efficiency modeling and its specifications. The results of the estimated efficiency level analyses show that smallholder cereal farmers in the study area were highly inefficient, which indicates that there was a lot of room for improvement using the present state of technology. For instance, the results of the OTE score simply that cereal farmers can increase their output by about 55 (43) per cent with (without) weather factors respectively, using their disposable resources more effectively (using the present state of technology).

Results from all inefficiency effects models show that most of the farmer-specific characteristics, adaptation strategies and agro-eco-climatic factors had significant effects in determining cereal farming technical (in) efficiencies. In particular, the MLE empirical results show that midland and highland AEZs and altitude related negatively and significantly to persistent inefficiencies. Similarly, MLE's empirical results on the transient technical inefficiency effects show that transient inefficiency was positively and significantly affected by the age of the household head and head's secondary schooling and extreme temperature variations under both (full and short) specifications. However, transient inefficiency was negatively and significantly related to the gender of the household head, household size and the number of plots under the full specification. It was negatively and significantly related to remittances, annual average rainfall and average extreme temperature levels under the short specification. The magnitude of the marginal effects of MLE's results differs substantially within and among cereal farmers and they were interpreted for significant variables for each (in) efficiency component.

The empirical results of the OTE effects models show that OTE was significantly enhanced by farm size, gender, household size, remittances, improved adaptation strategies (extension services, soil conservation, water harvesting and irrigation) and agro-ecological and climatic factors. Hence, these variables enhanced OTE, ceteris paribus. However, it was negatively influenced by credit use, age, tertiary education, off/non-farm activities and extreme weather variations. Hence, an increase in these factors reduced OTE ceteris paribus during the study period. In sum, despite the results of the weather factors in the context or trends of annual weather factors' distributions in the study area, the findings conclude a negative impact of the precipitation variables on cereal production and cereal productive efficiency while the opposite is true for the temperature variables.

Out of the set of regional dummy variables included in the regression to account for location differences, also proxied for soil types and quality, the variables highland and midland AEZs considerably affected cereals' OTE significantly and positively. Similarly, the variable altitude influenced technical inefficiency negatively and significantly. Hence, farming in midland or highland areas as compared to lowland areas contributed to an increase in overall cereal productive efficiency. Therefore, efficient production is likely to be in areas at mid to higher altitudes where rainfall and temperature are favorable for cereal crop production.

Further, the study also showed that neglecting heterogeneity such as environmental conditions (weather and/or agro-ecological factors) in the model's specifications, could lead not only to less precision of the model which may be due to omitted variables' bias in the frontier model, but also to significantly inflated estimates of technical efficiency and to a bias in the correlates of technical inefficiency effects, hence resulting in inconsistent effects as compared to their true values. Hence, in sum, the study concludes that omission/inclusion of climatic conditions/factors in the model's specification could not only affect the model's precision/fitness, but in addition it could also result in downward (upward) biases in technical (in)efficiency estimates and in biased estimates of the correlates of estimated technical inefficiency effects as well.

These findings are important and can be used to initiate government policy options to reduce farmers' inefficiencies by appropriately tackling sources of persistent and transient technical inefficiencies in particular and overall technical inefficiency in general. Policymakers should be aware of short-term and long-term policy options such as where to emphasize when planning climate change adaptation strategies and ways of promoting smallholder cereal productive efficiencies that are tailored to the peculiarities of the agro-ecological zones across the country. This essay recommends policies that will help improve production inputs supply and sustain improved adaptation strategies suitably designed to meet the needs of different agro-ecological areas to enhance short-term and long-term productive efficiencies of smallholder farmers.

References

African Development Bank (AfDB) (2016). *Federal Democratic Republic of Ethiopia: Country Strategy Paper-CSP*, 2016-20.

Aigner, D. J. and Chu, S. F. (1968). On estimating the industry production function. *American Economic Review, 58*(4): 826-39.

Aigner, D., C. K. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production model. *Journal of Econometrics*, 6(1): 21-37.

Badunenko, O. and S.C. Kumbhakar (2016). When, where and how to estimate persistent and transient efficiency in stochastic frontier panel data models. *European Journal of Operational Research*, 255: 272–87.

Baltagi, Badi H. (2008). *Econometric Analysis of Panel Data* (Fourth ed.). Chichester: John Wiley & Sons.

Bamlaku B.A., E.A. Nuppenau, and H. Boland (2009). Technical Efficiency of Farming Systems across Agro Ecological Zones in Ethiopia: An Application of Stochastic Frontier Approach. *Agricultural Journal*, 4(4): 202-7.

Banker, R. D. and R. Natarajan (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research*, 56: 48-58.

Barnwal, P. and K. Kotani (2013). Climatic impacts across agricultural crop yield distributions: an application of quartile regression on rice crops in Andhra Pradesh, India. *Ecological Economics*, 87: 95-109.

Battese, G.E. and T.J. Coelli (1988). Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. *Journal of Econometrics* 38 (3): 387–99.

Battese, G.E. and T.J. Coelli (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis*, 3: 153-169.

Battese, G.E. and T.J. Coelli (1995). Models for technical inefficiency in a stochastic frontier production function for panel data. *Empirical Economics*, 20: 325-32.

Belotti, F., S. Daidone, G. Ilardi, and V. Atella(2012). Stochastic frontier analysis using Stata.*Stata Journal*, 2: 1–39.

Berisso, O. M. (2017). 'Impact of Weather Variations on Cereal Productivity and Influences of Agro-ecological Differences in Ethiopian Cereal Production', in A. Heshmati (ed.), *Economic Transformation for Poverty Reduction in Africa*. London: Routledge, pp. 9-35.

Beyan, A., H. Jema, and G. Endrias (2013). Analysis of Farm Households' Technical Efficiency in Production of Smallholder Farmers: The Case of Girawa District, Ethiopia. *American-Eurasian Journal of Agricultural and Environmental Science*, 13(12): 1615-21.

Bravo-Ureta, and B. Evenson, (1994). "Efficiency in Agricultural Production: The Case of Peasant Farmers in Eastern Paraguay." Agricultural Economics 10: 27-37.

Chou, C., C. A. Chen, P. H. Tan, and K. T. Chen (2012). Mechanisms for global warming impacts on precipitation frequency and intensity. *Journal of Climate*, 25(9): 3291-306.

Colombi, R., S.C. Kumbhakar, G. Martini, and G. Vittadini (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis*, 42: 123-36.

Dhungana, B.R., Nuthall, P.L., Nartea, G.V., 2004. Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis. The Australian Journal of Agricultural and Resource Economics 48 (2), 347-369.

Farrell, M.J. (1957). Measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3): 253–81.

Filippini, M., W. Greene, and G. Masiero (2016). Persistent and Transient Productive Inefficiency in a Regulated Industry: Electricity Distribution in New Zealand. Università della Svizzera italiana: IdEP Economic Papers, No. 3, ETH Zurich, Switzerland.

Greene, W. (2005a). Reconsidering heterogeneity in panel data estimators of the stochastic frontier models. *Journal of Econometrics*, 126(2): 269–303.

Greene, W. (2005b). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis*, 23: 7-32.

Haji, J. (2006). Production Efficiency of smallholders' vegetable-dominated Mixed Farming System in Eastern Ethiopia: A non-parametric Approach. Journal of African Economies 16(1), 1-27.

Harris, I., P. D. Jones, T. J. Osborn, and D. H. Lister (2014). Updated high-resolution grids of monthly climatic observations–the CRU TS3, 10 Dataset. *International Journal of Climatology*, 34(3): 623-42.

Heshmati, A., S.C. Kumbhakar, and J. Kim (2017). Persistent and Transient Efficiency of International Airlines. *European Journal of Transport and Infrastructure Research*, forthcoming.

Heshmati, A., S.C. Kumbhakar, and L. Hjalmarsson (1995). Efficiency of Swedish pork industry: A farm level study using rotating panel data 1976-1988. *European Journal of operational Research*, 80: 519-33.

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modeling the DEA scores. *European Journal of Operational Research*, 181: 425-35.

Huang, C.J., and J.T. Liu (1994). Estimation of a non-neutral stochastic frontier production function. *Journal of Productivity Analysis,* 5: 171–80.

Jondrow, J., C.A.K. Lovell, I. S. Materov, and P. Schmidt (1982). On the estimation of technical inefficiency in stochastic frontier production model. *Journal of Econometrics*, 19: 233-38.

Karagiannis, G. and A. Sarris (2005). Measuring and Explaining Scale Efficiency with the parametric Approach: the Case of Greek Tobacco Growers. *Agricultural Economics*, 23: 441-51.

Kumbhakar, S.C. and A. Heshmati (1995). Efficiency measurement in Swedish dairy farms: An application of rotating panel data. *American Journal of Agricultural Economics*, 77: 660–74.

Kumbhakar, S.C., G. Lien, and J.B. Hardaker (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis*, 41(2): 321-37.

Kumbhakar, S.C., H. J. Wang, and A.P. Horncastle (2015). *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*. NY: Cambridge University Press.

Kumbhakar, S.C., S. Ghosh, and J.T. McGuckin (1991). A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business and Economic Statistics,* 9: 279–86.

Kurukulasuriya, P. and R. Mendelsohn (2008). A Ricardian Analysis of the Impact of Climate Change on African Cropland, *African Journal of Agricultural and Resource Economics,* 2(1), 1-23.

Lai, H.P. and S.C. Kumbhakar (2016). Panel Data Stochastic Frontier Model with Determinants of Persistent and Transient Inefficiency, Economics seminars papers, New York.

Madau, F. A. (2011). Parametric Estimation of Technical and Scale Efficiencies in Italian Citrus Farming. *Agricultural Economics Review*, 12 (1): 91-112.

McDonald, J. (2008). *Allowing for different frontier and sub-frontier relationships in second stage DEA efficiency analyses*. Adelaide: Flinders University.

Ministry of Finance and Economic Development (MoFED) (2010). *Growth and Transformation Plan I.* Volume 1. Addis Ababa: The Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development.

Mukherjee, D., B. E. Bravo-Ureta, and A. de Vries (2013). Dairy productivity and climatic conditions: Econometric Evidence from South-eastern United States. *Australian Journal of Agricultural and Resource Economics*, 57(1): 123-40.

Nyagaka, D. O., Obare, G. A., Omiti, J. M., & Nguyo, W. (2010). Technical efficiency in resource use: Evidence from smallholder Irish potato farmers in Nyandarua North District, Kenya. African Journal of Agricultural Research, 5(1), 1179–1186.

Ogada, M., J. Muchai, D. Mwabu, and M. Mathenge (2014). Technical efficiency of Kenya's smallholder food crop farmers: Do Environmental Factors Matter? *Environment Development and Sustainability,* 16 (5): 1065–76.

Parikh, A. and K. Shah (1994). Measurement of Technical Efficiency in the North-West Frontier Province of Pakistan. *Journal of Agricultural Economics*, 45: 132-38.

Reifschneider, D. and R. Stevenson (1991). Systematic departures from frontier: a framework for the analysis of firm inefficiency. *International Economic Review*, 32:715–23.

Reinhard, S., C.A.K. Lovell, and G.J. Thijssen (2002). Analysis of environmental efficiency variation. *American Journal of Agricultural Economics*, 84: 1054-65.

Schmidt, P. and R.C. Sickles (1984). Production frontier and panel data. *Journal of Business and Economic Statistics*, 2(4): 367–74.

Schultz, T.W. (1964). *Transforming Traditional Agriculture*. New Haven: Yale University Press.

Sherlund, S.M., C.B. Barrett, and A.A. Adesina (2002). Smallholder technical efficiency controlling for environmental conditions. *Journal of Development Economics*, 69: 85–101.

Simar, L. and P. Wilson (2007). Estimation and Inference in Two-stage, Semi-parametric Models of Production Processes. *Journal of Econometrics*, 136: 31-64.

Tchale H. and J. Suaer (2007). The Efficiency of Maize Farming in Malawi: A Bootstrapped Translog Frontier. *Cahiers d'economieet sociologierurales*, 1: 82-83.

Temesgen B., and Ayalneh B., (2005). Technical efficiency of recourse use in the production of irrigated potato in Awi Zone, Ethiopia. Journal of Agriculture and Rural Development in the Tropics and Subtropics: 106(1), 59-70.

The World Bank (2006). *Managing water resources to maximize sustainable growth: a country water resources assistance strategy for Ethiopia*. Washington, DC: The World Bank.

The World Bank (2010). *The World Bank annual report 2010.* Washington, DC: The World Bank Group.

Wadud, A., & White, B. (2000). Farm household efficiency in Bangladesh: A comparison of stochastic frontier and DEA methods. *Applied Economics*, 32, 1665–1673.

Wooldridge, J.M. (2002). *Econometric analysis of cross-section and panel data*. Cambridge, Massachusetts: The MIT Press.

APPENDIX: SURVEY QUESTIONNAIRE

ETHIOPIAN RURAL HOUSEHOLD SURVEY, 2015
QUESTIONNAIRE FOR THE EIGHTH ROUND

DEPARTMENT OF ECONOMICS, ADDIS ABABA UNIVERSITY, in collaboration with the Environment and Climate Research Centre (ECRC) at Ethiopian Development Research Institute (EDRI), Ethiopia.

Instructions to Enumerator: ***Dear Enumerator note that; the respondent for this questionnaire should be the HOUSEHOLD's HEAD from the roster card and several attempts should be made to ensure that the HEAD is interviewed. If this is not possible, the most knowledgeable person about these topics would be appropriate.***

Instructions to Respondent: ***Dear respected respondent*, the purpose of this questionnaire is to gather data for a research work to analyze *Impact of Climate Variation on Productivity, Efficiency, Food Security and Adaptation Technologies in Ethiopia's Cereal Crop Producers*". The survey is being conducted in 18 PAs in 18 Woredas (Districts) in 4 Regional States (TIGRAY, AMAHARA, OROMIIA and SNNP) in Rural Ethiopia, focusing on household's demographic characteristics, agricultural production inputs use and outputs, access to institutions, household's consumption patterns and climate change information. The information you are going to provide will be used purely for research purpose. Thus, we would kindly request you to respond honestly to items given below. Your cooperation is very critical and compulsory to achieve the desired objectives of the research. Your responses will be very confidential and will only be used for research purpose. Finally, we would like to thank you for your genuine, unreserved and valuable responses you made as required.**

INTERVIEWER'S NAME					
DATE OF INTERVIEW	DAY		MONTH		YEAR (EC)

REGION CODE NUMBER		NAME OF PA		NAME OF THE RESPONDENT (if not the Household's Head)	
WOREDA CODE NUMBER		PA'S CODE NUMBER		NAME OF VILLAGE/NEIGHBOURHOOD WITHIN PA	
		NAME OF SURVEY SITE		NAME OF NEAREST TOWN TO YOUR VILLAGE?	
		NAME OF HOUSEHOLD'S HEAD		DISTANCE OF THE TOWN: FROM YOUR VILLAGE (in km)?	

Age of the Household's Head:		Sex of the Household's Head: **Male 1 Female 2**		
Educational Level of Household's Head **-** Highest grade completed. **Code (c):**See next page		Marital status of Household's Head. **Code (b):*See next page***		
Is this the same Household Head as appearing on the roster card for the previous round **YES 1 NO 2**		Total family size of the Households Currently Existing or living in the Household (including HH's Head).	**M =**	**F =**

Interview Log	Check off if Complete	Any problems 1 No (or few) problems 2 Respondent had some difficulty answering these questions 3 Respondent had considerable difficulty answering these questions	Checked by supervisor
Voluntary Consent Obtained			
Part I			
Part II			
Part III			

CHECKS (put crosses if applicable)

DATE CHECKED	CHECKER INITIALS	STATUS		PROBLEM	COMMENTS	CORRECTED?
		OK	RETURN			

PART I -*CONTAINS four SECTIONs*: HOUSEHOLD DEMOGRAPHICS, NON-FOOD EXPENDITURES, OFF-FARM INCOME AND BUSINESS ACTIVITIES; and CREDIT

CODES FOR PART I, SECTION 1

Code (a), Relationship to Head	
1 Head	9 Son/Daughter-in-law
2 Wife/Husband	10 Father/Mother-in-law
3 Son/daughter	11 Brother/Sister-in-law
4 Grandchild	12 Grandparent
5 Father/Mother	13 Other relative of head or of his/her spouse
6 Sister/Brother	14 Servant (farm worker, herder, maid, etc.)
7 Niece/nephew	16 Other unrelated person
8 Uncle/Aunt	

Code (b), Marital Status
1 Married, Single Spouse
2 Single
3 Divorced
4 Widowed
5 Not together for any reason
6 Married, more than one Spouse

Code (c), Highest Grade Obtained or Completed		
0 Did not complete any schooling	7 7th Grade	13 Incomplete higher education (not university)
1 1st Grade	8 8th Grade	14 Completed higher education (not university)
2 2nd Grade	9 9th Grade	15 Incomplete university education
3 3rd Grade	10 10th Grade	16 Completed university education
4 4th Grade	11 11th Grade	17 Adult literacy program participation
5 5th Grade	12 12th Grade	18 Other literacy program
6 6th Grade		19 Some Church/Mosque School
		30 Other

PART I, SECTION 1: HOUSEHOLD DEMOGRAPHICS, CONTINUING MEMBERS *and* NEW MEMBERS (for the HOUSEHOLDS ON the ROSTER CARD)

For each member of the Household, starting from the Household Head list their names, first those of individuals that present in Round 7 (i.e. present in EC2001) and ***currently present only,***in the 1st column below. Next for all persons who are ***new members to the household since EC 2001***(i.e., who entered the household after EC 2001), assign them new ID codes (as 81, 82, 83…) and list their name. Then for each person listed, ask the respondent to answer the following questions.

Household Member ID Codes	Name	1. What is the relationship of .[NAME]; to the head? Code (a)	2. What is his/her age?	SEX MALE...1 FEMALE…..2	3. Marital status Code (b)	5 What is the highest grade of schooling ... [NAME] ..has obtained or completed so far? Code (c)
1						
2						
3						
4						
5						
6						
7						
8						
81						
82						
83						
84						

CODES FOR PART I, SECTION 2: NON-FOOD EXPENDITURE and SECTION 3: OFF-FARM INCOME & BUSINESS ACTIVITIES

Code (a), Type of Employment /Work	Code (b), Location of Work/Sale/Purchase	Code (c), Months		Code (d), Source of GIFT
1 FARM WORKER (FOR PAY)	1 THIS VILLAGE	1 MESKEREM	7 MEGABIT	1 NON-RESIDENT HOUSEHOLD MEMBER
2 TRADITIONAL LABOUR SHARING (FARM WORK)	2 ANOTHER VILLAGE	2 TIKMIT	8 MIAZIA	2 RELATIVE
3 PROFESSIONAL (Teacher, Health Worker ,Government Worker)	3 LOCAL MARKET TOWN	3 HIDAR	9 GUENBOT	3 FRIEND/NEIGHBOUR
4 SKILLED LABOURER (IE BUILDER, THATCHER, MASON, ETC)	4 REGIONAL CENTER	4 TAHSAS	10 SENE	4 FROM EQUB
5 TRADER	5 ADDIS ABABA	5 TIR	11 HAMLE	5 FROM IDDIR
6 SOLDIER	6 OUT OF ETHIOPIA	6 YEKATIT	12 NAHASSIE	6 GIFT FROM CHURCH/MOSQUE/RELIGIOUS ORGANISATION
7 DRIVER/MECHANIC	7. OTHER (SPECIFY)		13 PAGUME	7 GIFT FROM OTHER LOCAL ORGANISATION
8 UNSKILLED non-farm worker				8 FROM A BANK
9 DOMESTIC SERVANT (YEBET SERATEGNA)				9 FROM GOVERNMENT/MINISTRY/KEBELE
10 FOOD-FOR-WORK				10 FROM NGO
11 OTHER				11 FROM ABROAD OR INTERNATIONAL
				12 OTHER (SPECIFY)

Code (e) CROP CODES (or ITEM CODES)

1 WHITE TEFF	17 CHAT	33 GARLIC (NechShinkurt)	49 CABBAGE (Gomen)	65 MILK/YOGHOURT	83 SPICES
2 BLACK/MIXED TEFF	18 ENSET	34 YAM	50 PADDY, RICE	67 CHICKEN	84 KARIA
3 BARLEY (Gebis)	19 BANANAS	35 FASOLIA	51 SINAR/GERIMA	68 EGGS	85 BERBERE
4 WHEAT (Durrah, Sinde)	20 GRASS	36 FRUIT	52 HARICOT BEANS (Boloke)	70 TELLA	86 BREAD (DABO)
5 MAIZE (Bekolo/Bahirmashla)	21 GESHO	37 MANGO	53 FIELD PEAS	71 TEJ	87 MACARONI/SPAGHETTI
6 SORGHUM / Mashila	22 EUCALYPTUS	38 HAMICHO	54 FENUGREEK (Abish)	72 BIRRA (Bottled)	88 KARIBO/KEREDO
7 ZENGADA	23 SHIEFERA/HALEKO	39 KOCHO	55 BEET ROOT (Key Sir)	73 ARAQI/KATHIKALA	89 TURMERIC (Ird)
8 OATS	24 DAGUSSA	40 CHICK PEAS (Shimbra)	56 CARROT	74 SOFT DRINKS	90 COFFEE LEAF / TEA / ASHARA
9 HORSE BEANS (Bakela)	25 SUNFLOWER	41 COW PEAS (Ater)	57 GINGER (Jinjibel)	75 SUGAR	
10 LINSEED (Telba)	26 POTATOES	42 ORANGE	58 SELATA (Lettuce)	76 HONEY	91 CACTUS (beles/fruit/ leaves)
11 GROUNDNUTS (Lew)	27 SUGARCANE	43 GODERE	59 TIKL GOMMEN	81 SALT	95 Other
12 SESAME (Selit)	28 TOBACCO	44 ADENGUARE	60 PUMPKIN (Duba)	82 COOKING OIT/ EDIBLE OIL	
13 BLACK PEPPER (Kundoberbere)	29 PINEAPPLE (Ananas)	45 SWEET POTATOES	61 BEEF (Yekebit Sega)		
14 LENTILS (Mesir)	30 AVOCADO	46 TOMATO	62 MUTTON (Yegeb)/ GOAT MEAT (YefiyelSiga)		
15 VEGETABLES	31 ONIONS (Shinkurt)	47 GUAYA (Vetch)	63 SHIRO/KOLLO		
16 COFFEE	32 SPINACH (Quosta)	48 NUEG	64 BUTTER/CHEESE		

Code (f) QUANTITY UNITS

1 KILOGRAMMES	11 BOBO	21 GAN	40 BIG MADABERIA	50 BUNCH (BANANAS)	60 EGIR
2 QUINTAL	12 PACKETS	22 ENSIRA	41 SMALL MADABERIA	51 MELEKIA/LIK	61 WESLA
3 CHINET	13 BAGS	23 GURZIGNE	42 DIRIB	52 GUCHIYE	62 MESFERIA
4 DAWLA	14 BUNDLES	24 TASSA	43 SAHIN/LOTERY	53 BEKOLE	63 KURFO
5 KUNNA	15 PIECES	25 KUBAYA/KELASA	44 MANKORKORIA	54 ENKIB	64 KOLELA
6 MEDEB	16 BARS	26 BIRCHIKO	45 PLATIC BAG/FESTAL	55 SHEKIM	
7 KURBETS	17 BOXES	27 SINI	46 ZURBA	56 NUMBER	95 OTHER (Specify)
8 SILICHA	18 LEAVES	28 GEMBO	47 AKARA	57 GOTERA	
9 AKMADA	19 LITRES	29 BOTTLES	48 SMALL PLASTIC BAG (MIKA)	58 LEMBA	
10 ESIR	20 KIL	30 BIRR	49 KERCHAT/KEMBA	59 SHIRIMERI	

Code (g), Type of receipt
1a.REMITTANCE from (National/Local or with in Ethiopia)
1b. REMITTANCE from (Abroad or Out of Ethiopia)
2 GIFT
3 INHERITANCE
5 OTHER TRANSFER
6 DOWRY
7 TRANSFER FOR SCHOOL COSTS
9 COMPENSATION

PART I, SECTION 2: NON-FOOD EXPENDITURE

IN THE LAST FOUR MONTHS, has the Household purchased any of the following non-food items? OR has the Household spent on any of the following items? ;

Item	Code	2. Total expenditure in the last four months (in BIRR)	3. Where purchased Code (b)		Item	Code	2. Total expenditure in the last four months (in BIRR)	3. Where purchased Code (b)
Clothes/shoes/fabric for MEN	301				Modern medical treatment and medicines	401		
Clothes/shoes/fabric for WOMEN	302				Traditional medicine and healers	402		
Clothes/shoes/fabric for BOYS	303							
Clothes/shoes/fabric for GIRLS	304							
Kitchen equipment (cooking pots, etc.)	341				School fees	421		
Linens (sheets, towels, blankets)	342				Other educational expenses (exercise books, pens, pencils, uniforms)	422		
Furniture	343				Cigarettes, tobacco, suret, gaya	430		
Lamp/torch	344				Alcoholic beverages	432		
					Savings and credit scheme	433		
Transport	361				Repair and maintenance	434		
Building materials	362				Chat	435		
Ceremonial expenses	381				Cosmetics (Hair oil, butter, perfume)	439		
Contributions to IDDIR	382				Bicycle	445		
Donations to the church	383				Bio-Gas tube (Oxygen gas)	446		
					Labour cost/salary	448		
Taxes and levies	391				Mencha	449		
Compensation and penalty	392							
Voluntary contributions	393							
Baby clothes (including Aneklba)	305							
Umbrella	306							
Sieve (Wonfiet), Gourd (Kil), Sefed, Mesob, Jeri-can, Sini, etc.	341							
Jeba, Gembo, Mitad, Broom and other such items	341							
Rent	363							
Gold, dowry for spouse (ceremonial expenses)	381							
Donation to mosque	383							
Other contributions to a person (including Erteban)	384							
Payment to broker	391							
Compensation and/or penalties	392							
Involuntary (forced contributions	394							

Expenses for household consumables, such as kerosene, matches, laundry soap, etc., should not be reported here. They are reported in Part III, Section 1.

PART I, SECTION 3: OFF-FARM INCOME AND BUSINESS ACTIVITIES

1a. In the last 12 (13 Ethiopian) months, did you or any other members of the household work off the household's land either on someone else's land or in some other employment, ***against payment in cash or in kind***, including as part of food for work, or as part of a labour sharing agreement (debbo, wonfel, etc.)? **YES ….1 NO …..2**	
1b. IN THE LAST FOUR MONTHS, did you or any other members of the household work off the household's land either on someone else's land or in some other employment, ***against payment in cash or in kind***, including as part of food for work, or as part of a labour sharing agreement (debbo, wonfel, etc.)? **YES ….1 NO …..2**	
IF 1a and 1b are YES, proceed to answer Q_2 – Q_7 ; IF 1a and 1b are NO, skip to next page	

2 ID CODE of household member **(see from section 1)**	3 Specify the kind of of employment /work **Code (a)**	4 Location of of employment /work **Code (b)**	5 Days worked IN THE LAST FOUR MONTHS? If traditional labour sharing, mention number of days participated.		6 Total amount earned IN THE LAST FOUR MONTHS. If in kind, give amount, form of payment and unit.				7 In the last 12 (13 Ethiopian) MONTHS, how many months have you been involved in this activity for more than 5 days (number)
			Days worked for pay (cash or in kind)	Traditional labour sharing (debbo) (Number of days participated)	AMOUNT IN BIRR	AMOUNT IN KIND	IN KIND FORM **Code (e)**	Unit **Code (f)**	

PART I, SECTION 3: OFF-FARM INCOME AND BUSINESS ACTIVITIES continued …

We would like to ask you about other income earning activities, such as crafts, trades and other business, carried out by you or any other member of the household.

8a. In the last 12 (13 Ethiopian) months, have you or other members of your household been involved in any of the activities listed below? **1 YES 2 NO**	
8b. IN THE LAST FOUR MONTHS, have you or other members of your household been involved in any of the activities listed below? **1 YES 2 NO**	
IF 8a and 8b are NO, skip to next page. ; IF 8b is YES, go to Q_9 – Q_{11} ; IF 8a is YES and 1b is NO, go to Q_{12}	

ACTIVITY	**Code**	9 Household member responsible (ID CODE) **(see from section 1)**	10 How much has the household earned (net of costs) from this activity IN THE LAST FOUR MONTHS? AMOUNT IN BIRR	AMOUNT IN KIND	FORM IN KIND **Code (e)**	UNIT **Code (f)**	11 Location of sales **(Code b)**	12 In the last 12 (13 Ethiopian), how many months were you involved in this activity?
Weaving/spinning	25							
Milling	26							
Handicraft, incl. pottery	27							
Trade in grain/general trade (incl. banana, pepper, honey, etc.)	28							
Trade in livestock/livestock prod.	29							
Traditional healer/religious teacher	30							
Transport (by pack animal)	32							
Collecting, selling firewood or dung cakes	33							
Other activities? Specify _________________________								

13. Has the household RECEIVED any other income (such as remittances from friends/relatives, gifts, food aid/other aid, payment for health or education, any other transfers) IN THE LAST 12 (13 ETHIOPIAN) MONTHS? (**From within the Country Or From Abroad/Out of Ethiopia**)**1 YES 2 NO** IF YES, GIVE DETAILS FOR EACH TRANSFERIN THE TABLE BELOW (**Q_{14-19}**) ; IF NO FOR ALL HOUSEHOLD MEMBERS, GO TO THE NEXT PAGE	

14 EACH TRANSFER RECEIVED IS SEPARATE ROW	15 TYPE OF RECEIPT **Code (g)**	17. Who sent you the transfer? **Code (d)**	18. Where does this person live/ is organisation based? **Code (b)**	19. Give the month when you were given the remittances or gift and the amount involved. Give amount in Birr; if in kind, please give amount in kind, form of payment and unit. **MONTH Code (c)**	**AMOUNT IN BIRR**	**IN KIND AMOUNT**	**IN KIND ITEM Code (e)**	**Unit Code (f)**
1								
2								
3								
4								

CODES FOR PART I, SECTION 4: CREDIT

Code (a): Why No Loan Was Taken
1 NO NEED FOR A LOAN
2 TRIED TO GET A LOAN BUT WAS REFUSED
3 NO-ONE AVAILABLE TO GET A LOAN FROM
4 EXPECTED TO BE REJECTED, SO DID NOT TRY TO GET ONE
5 I HAVE NO ASSETS FOR COLLATERAL
6 AFRAID OF LOSING COLLATERAL
7 AFRAID THAT I CANNOT PAY BACK
8 INTEREST RATES TOO HIGH
9 OTHER

Code (e): Months	7 MEGABIT
1 MESKEREM	8 MIAZIA
2 TIKMIT	9 GUENBOT
3 HIDAR	10 SENE
4 TAHSAS	11 HAMLE
5 TIR	12 NAHASSIE
6 YEKATIT	13 PAGUME

Code (b): Source of Loan
1 MONEYLENDER/ARATA
2 RELATIVE
3 FRIEND/NEIGHBOUR
4 FROM EQUB
5 FROM IDDIR
6 FROM THE COOPERATIVE
7 LOAN FROM OTHER LOCAL ORGANISATION
8 FROM A BANK
9 FROM GOVERNMENT/MINISTRY/KEBELE
10 FROM MICROCREDIT PROGRAM / NGO
11 OTHER (SPECIFY)

Code (c): Location
1 THIS VILLAGE
2 ANOTHER VILLAGE
3 LOCAL MARKET TOWN
4 REGIONAL CENTER
5 ADDIS ABABA
6 OTHER (SPECIFY)

Code (d): Reason for Loan
1 TO BUY FARM OR OTHER TOOLS/IMPLEMENTS
2 TO BUY INPUTS E.G SEEDS/FERTILISER/PESTICIDES
3 TO BUY LIVESTOCK
4 TO PAY FOR HIRED LABOUR
5 TO PAY RENT/TAXES
6 TO START AN OFF-FARM BUSINESS (LIKE WEAVING)
7 TO BUY FOOD/GOODS FOR THE HOUSEHOLD
8 TO PAY FOR TRAVEL EXPENSES
9 TO PAY FOR BUILDING MATERIALS
10 TO PAY FOR HEALTH EXPENSES
11 TO PAY FOR EDUCATION EXPENSES
12 FOR WEDDING
13 FOR FUNERAL
15 REPAY OTHER DEBTS
20 OTHER

Code (e) : CROP CODES (or ITEM CODES) - See page 3

Code (f): QUANTITY UNITS - See page 3

PART I, SECTION 4: CREDIT….[*Please use code (e) and (f) from page 3*]

1. IN THE 12 (13 ETHIOPIAN) MONTHS, have you taken out a loan of at least 20 Birr, in cash or IN KIND? **1 YES** (If yes, go to question 3 - 7 to obtain details). **2 NO**	
2. If not, Why did you not take a loan? **code (a):** ________ And then Go to question 8 & 9	

If yes, please give details about these loans. Include those you have paid back, as well as loans you have not paid back as yet.

Loan number EACH LOAN IS SEPARATE LINE GIVE DETAILS ON ALL LOANS	3. ID code of person receiving loan	4. SOURCE OF LOAN **Code (b)**	5. Location of lender? **Code (c)**	6. Why did you want to obtain a loan? **Code (d)**	7. Give the month when you took out the loan and the amount borrowed. Give amount in Birr; if in kind, please give amount in kind, form of payment and unit.				
					MONTH **Code (e)**	**AMOUNT IN BIRR**	**IN KIND AMOUNT**	**IN KIND CROP:** ***Use* Code (e)*-from page 3***	**Unit *Use* Code (f)- *from page 3***
1									
2									
3									

8. Does any member of the household have a saving bank account? YES….1 NO……2 ______________

9. Are you and/or members of your household is a member of any of the following? **YES….1 NO……2**	Eqqub	Iddir	Credit and saving cooperative	Producer/Service cooperative	Micro & Small Ent.	Others (specify)

PART II: AGRICULTURE- CONTAINS *six* SECTIONs:

The respondent for this part of the questionnaire (PART II) should be the male member of the household who answered Part I.

CODES FOR PART II, SECTION 1: (For SECTIONs: 1A, 1B, and 1C)

Code (a) Land units	
1	GASHA
2	HECTARE
3	GEMED
4	TIMAD
5	KERT
6	MASSA
7	KEDEMA
8	KUFARO
9	ZHIR
10	OTHER____
13	TINTO
14	ERMIJA
15	DERO
16	GEZEM
17	KEND
18	SQUARE ZHIR
19	MEDEB
20	SQUARE METER
22	BOY

Code (b) Soil quality	
1	LEM
2	LEM-TEUF
3	TEUF

Code (c) Slope of plot	
1	MEDDA
2	DAGATH-AMA
3	GEDDEL

Code (k) location of sale?	
1	THIS VILLAGE
2	ANOTHER VILLAGE
3	LOCAL MARKET TOWN
4	REGIONAL CENTER
5	ADDIS ABABA
6	OTHER (SPECIFY)

	Code(d) Land use
1	CULTIVATED BY THE HOUSEHOLD
2	GRAZING LAND
3	LEFT FALLOW FOR THE ENTIRE YEAR
4	RENTED OUT TO ANOTHER HOUSEHOLD
5	SHARECROPPED OUT TO OTHER HOUSEHOLD
6	LENT TO OTHER HOUSEHOLD
7	WOODLAND
8	OTHER ___________

	Code (e) Crop Codes/Types		
1	WHITE TEFF	32	SPINACH (Quosta)
2	BLACK/MIXED TEFF	33	GARLIC (NechShinkurt)
3	BARLEY (Gebis)	34	YAM
4	WHEAT (Durrah, Sinde)	35	FASOLIA
5	MAIZE (Bekolo/Bahirmashla)	36	FRUIT
6	SORGHUM / Mashila	37	MANGO
7	ZENGADA	38	KOCHO
8	OATS	39	HAMICHO
9	HORSE BEANS (Bakela)	40	CHICK PEAS (Shimbra)
10	LINSEED (Telba)	41	COW PEAS (Ater)
11	GROUNDNUTS (Lew)	42	ORANGE
12	SESAME (Selit)	43	GODERE
13	BLACK PEPPER	44	ADENGUARE
14	LENTILS (Mesir)	45	SWEET POTATOES
15	VEGETABLES	46	TOMATO
16	COFFEE	47	GUAYA (Vetch)
17	CHAT	48	NUEG
18	ENSET	49	CABBAGE (Gomen)
19	BANANAS	50	PADDY, RICE
20	GRASS	51	SINAR/GERIMA
21	GESHO	52	HARICOT BEANS (Boloke)
22	EUCALYPTUS	53	FIELD PEAS
23	SHIEFERA/HALEKO	54	FENUGREEK (Abish)
24	DAGUSSA	55	BEET ROOT (Key Sir)
25	SUNFLOWER	56	CARROT
26	POTATOES	57	GINGER (Jinjibel)
27	SUGARCANE	58	SELATA (Lettuce)
28	TOBACCO	59	TIKL GOMMEN
29	PINEAPPLE (Ananas)	60	PUMPKIN (Duba)
30	AVOCADO	95	OTHER
31	ONIONS (Shinkurt)		

Code (g): Reason for change of cultivating land size	
1	LAND REDISTRIBUTION (SHIGISHIG) BY KEBELE
2	LAND INHERITANCE OR SHARING WITHIN FAMILY
3	LAND EROSION
4	SHARECROPPING OR RENTING OF LAND
5	OTHER ____________

	Code (h) how acquired?
1	ALLOCATED
2	PURCHASED
3	INHERITED/PARENTS' GIFT
4	MORTGAGED/PLEDGED
5	RENTED IN
6	SHARECROPPED IN
7	BORROWED FREE

	Code (i) From Whom acquired?
1	PEASANT ASSOCIATION
2	HUSBAND'S PARENTS
3	WIFE'S PARENTS
4	RELATIVE
5	NON-RELATIVE
6	OTHER _____________

	Code (j) to Whom can you give plot?
1	TO ANYONE
2	ONLY TO CHILD OF HEAD OF HOUSEHOLD
3	ONLY TO OTHER RELATIVE
4	Other _________________

Code (f) QUANTITY UNITS

1 KILOGRAMMES	10 ESIR	19 LITRES	28 GEMBO	46 ZURBA	51 MELEKIA/LIK	60 EGIR
2 QUINTAL	11 BOBO	20 KIL	29 BOTTLES	47 AKARA	52 GUCHIYE	61 WESLA
3 CHINET	12 PACKETS	21 GAN	30 BIRR	48 SMALL PLASTIC BAG (MIKA)	53 BEKOLE	62 MESFERIA
4 DAWLA	13 BAGS	22 ENSIRA	40 BIG MADABERIA	49 KERCHAT/KEMBA	54 ENKIB	63 KURFO
5 KUNNA	14 BUNDLES	23 GURZIGNE	41 SMALL MADABERIA	46 ZURBA	55 SHEKIM	64 KOLELA
6 MEDEB	15 PIECES	24 TASSA	42 DIRIB	47 AKARA	56 NUMBER	
7 KURBETS	16 BARS	25 KUBAYA/KELASA	43 SAHIN/LOTERY	48 SMALL PLASTIC BAG (MIKA)	57 GOTERA	95 OTHER (Specify)
8 SILICHA	17 BOXES	26 BIRCHIKO	44 MANKORKORIA	49 KERCHAT/KEMBA	58 LEMBA	
9 AKMADA	18 LEAVES	27 SINI	45 PLATIC BAG/FESTAL	50 BUNCH (BANANAS)	59 SHIRIMERI	

PART II, SECTION 1A -LAND AND ITS USE: QUALITY OF LAND AND CROPS GROWN.

We would like to ask some questions about all the land used by your *BETESEB* during the last full agricultural year. Please include land you are cultivating that belongs to other households. Also include land that is your land but cultivated by other household. First, give details about the plots cultivated during the last 12 months. First mention the plots cultivated during the last Meher. Then mention all plots cultivated during the Belg. If some plots were cultivated during both the (equivalent of) Meher and Belg, mention them as one plot. A plot used for permanent crops is considered used for Meher and Belg. If they were cultivated with different crops during each season; on the line with the details about the plot, give the season and then the crops cultivated during the Meher and then the crops cultivated during the Belg in the following line. Mention also land used exclusively for woodland, livestock grazing or left fallow during the last 12 months. Finally, list all plots belonging to the household but rented out or sharecropped out and *used by another household*. Plots can be divided into parcels. A plot belongs to the same parcel if it is physically connected, and is not separated by a natural obstacle or by land from another farmer.

1 PLOT NO	2 PARCEL NO	3 Plot Size		4. Is the land Lem, Lem-teuf or teuf land? **Code (b)**	5. Slope of the plot? Medda, dagath-ama or geddel? **Code (c)**	Soil Type 1.Sandy 2. Clay 3. Rad 4. Black 5.Loam 6.Other	6. Land Use? (if fallow, grazing or woodland or cultivated by another HH -> next plot)	7 Season Meher…1 Belg……2 Both Meher and Belg……3	8, Please list the area allocated to each of the crops planted (***in particular starting from CEREAL CROPS***) on this plot. IF THE LAND IS INTERCROPPED, THEN THE TOTAL AREA SHOULD BE DIVIDED BY THE NUMBER OF CROPS GROWN ON THE PLOT. FOR PLOTS USED BOTH IN BELG AND IN MEHER, GIVE THE MOST RECENT CROP GROWN ON THE PLOT ON THE FIRST LINE, AND THE CROP DURING BELG ON THE NEXT LINE (UNDERNEATH). **Crop codes: (e)**; Under area give area planted with that crop. I-CROP=INTERCROPPED													
		AREA	Unit **(a)**						Crop no.1	AREA	Crop no.2	AREA	I-CROP WITH NO.1? **YES…..1 NO……..2**	Crop no.3	AREA	I-CROP WITH NO.2? **YES……1 NO…….2**	Crop no.4	AREA	I-CROP WITH NO.3? **YES...1 NO….2**	Crop no.5	AREA	I-CROP WITH NO.4? **YES…1 NO…..2**
01	01																					

PART II, SECTION 1B: LAND AND ITS USE: LAND ACQUISITION AND RIGHTS.
First copy the plot sizes (Q_3) from Part II section 1A. Then ask these questions *plot by plot.*

1 PLOT NO	2. PARCEL NO	3 Plot Size area	Unit **(a)**	4 When did you acquire the plot (EC)	5 How did you acquire the plot? **code (h)**	6 From whom did you acquire the plot? **code (i)**	9. FOR PLOTS SHARECROPPED IN If the plot is sharecropped and owned by another household, what was the household's share? (Write 0.50, 0.33, 0.66 etc.)	10. FOR PLOTS RENTED IN If the plot is rented, what was the rent (in birr) per year?	11. FOR PLOTS RENTED OUT OR SHARECROPPED OUT How much has the household received as rent in kind or in cash from the other household? Amount in birr	Amount in kind	Crop code for in-kind payment **Code (e)**	Unit **code (f)**
01	01											

PART II, SECTION 1C: LAND AND ITS USE: PLOT OUTPUT
***In particular starting from cereal crops (White &Black/Mixed Teff*, *Barley, Wheat, Maize, Sorghum, Millet /Zengada, Oats/Aja,).*FIRST COPY PLOT SIZE (Q_3), SEASON (Q_7) AND CROPS ON EACH PLOT (FROM Q_8) FROM Part II SECTION 1A.**

1 PLOT NO	2 PARCEL NO	3 Plot Size AREA	UNIT **(a)**	4 Season Meher 1 Belg…2 Meher and Belg…3	5 Crop on this plot **(e)**	TOTAL OUTPUT	UNIT **(f)**	Crop on this plot **(e)**	TOTAL OUTPUT	UNIT **(f)**	Crop on this plot **(e)**	TOTAL OUTPUT	UNIT **(f)**	Crop on this plot **(e)**	TOTAL OUTPUT	UNIT **(f)**	Crop on this plot **(e)**	TOTAL OUTPUT	UNIT **(f)**	6 Did you use fertiliser on this plot? (If yes Amount in KGs)	7 was the plot under new extension program? **YES…..1 NO……..2**

PART II, SECTION 1D: LAND AND ITS USE: PERMANENT TREE CROPS.*CODES FOR PERMANENT TREE CROPS*

16	COFFEE	18	ENSET	20	GRASS	22	EUCALYPTUS	27	SUGARCANE	29	PINEAPPLE(Ananas)	36	FRUIT	38	HAMICHO	95	OTHER
17	CHAT	19	BANANAS	21	GESHO	23	SHIEFERA/HALEKO	28	TOBACCO	30	AVOCADO	37	MANGO	42	ORANGE		

1. Does the household grow trees or tree crops? **Yes ... 1; No ... 2** (IF NO, GO TO NEXT SECTION).	

If **yes;** can we ask you about your tree and permanent crops, including coffee, chat or eucalyptus?
FOR THE QUESTIONS ASKING FOR 'PART OF YOUR TREES' WRITE THE PROPORTION AS A FRACTION OF THE NUMBER OF PLANTINGS, FOR EXAMPLE 1/3, 3/4, ETC. IF NONE, WRITE 0/0, IF ALL WRITE 1/1.
IF THE ANSWER IS GIVEN AS A NUMBER OF TREES, WRITE THE ANSWER IN THE NUMERATOR AND THE TOTAL NUMBER OF TREES ON THE FARM IN THE DENOMINATOR OF QUESTIONS 4, 5 AND 6.

Tree Crop **Code (a)**	2 How many of... [..].. Plants or trees does the farm have?**)**	3 Did you last plant any...? [..].. Plants or trees in the last FIVE YEARS? YES….1 NO…..2	NUMBER PLANTED IN LAST FIVE YEARS	4 What part of your ... [...]... is too young to produce?	5 What fraction of your ... [...]... is in full production?	6 What fraction of your ... [...]... is so old that it is no longer in full production?	7 How much or percentage of your of TOTAL LAND you acquired is covered by TOTAL TREE PLANTS including WOODY TREES or WOODLAND (**Use Percentage**)
				/	/	/	
				/	/	/	
				/	/	/	
				/	/	/	
				/	/	/	

PART II, SECTION 2: AGRICULTURAL INPUTS - LABOUR SHARING GROUPS, OTHER LABOUR (i.e. FAMILY and HIRED LABOUR) and OTHER EXPENDITURES
CODES FOR PART II, SECTION 2: AGRICULTURAL INPUTS – (For SECTIONs: 2A, 2B, and 2C)
Code (a) CROP CODES (or ITEM CODES)

1 WHITE TEFF	17 CHAT	33 GARLIC (Nech Shinkurt)	49 CABBAGE (Gomen)	65 MILK/YOGHOURT	83 SPICES
2 BLACK/MIXED TEFF	18 ENSET	34 YAM	50 PADDY, RICE	66	84 KARIA
3 BARLEY (Gebis)	19 BANANAS	35 FASOLIA	51 SINAR/GERIMA	67 CHICKEN	85 BERBERE
4 WHEAT (Durrah, Sinde)	20 GRASS	36 FRUIT	52 HARICOT BEANS (Boloke)	68 EGGS	86 BREAD (dABO)
5 MAIZE (Bekolo/Bahirmashla)	21 GESHO	37 MANGO	53 FIELD PEAS	69	87 MACARONI/SPAGHETTI
6 SORGHUM / Mashila	22 EUCALYPTUS	38 HAMICHO	54 FENUGREEK (Abish)	70 TELLA	88 KARIBO/KEREDO
7 ZENGADA	23 SHIEFERA/HALEKO	39 KOCHO	55 BEET ROOT (Key Sir)	71 TEJ	89 TURMERIC (Ird)
8 OATS	24 DAGUSSA	40 CHICK PEAS (Shimbra)	56 CARROT	72 BIRRA (Bottled)	90 COFFEE LEAF / TEA / ASHARA
9 HORSE BEANS (Bakela)	25 SUNFLOWER	41 COW PEAS (Ater)	57 GINGER (Jinjibel)	73 ARAQI/KATHIKALA	
10 LINSEED (Telba)	26 POTATOES	42 ORANGE	58 SELATA (Lettuce)	74 SOFT DRINKS	91 CACTUS (beles/fruit/leaves)
11 GROUNDNUTS (Lew)	27 SUGARCANE	43 GODERE	59 TIKL GOMMEN	75 SUGAR	95 Other
12 SESAME (Selit)	28 TOBACCO	44 ADENGUARE	60 PUMPKIN (Duba)	76 HONEY	
13 BLACK PEPPER (Kundoberbere)	29 PINEAPPLE(Ananas)	45 SWEET POTATOES(SekuarDinich)	61 BEEF (Yekebit Sega)	81 SALT	
14 LENTILS (Mesir)	30 AVOCADO	46 TOMATO	62 MUTTON (Yegeb)/GOAT MEAT(YefiyelSiga)	82 COOKING OIT/ EDIBLE OIL	
15 VEGETABLES	31 ONIONS (Shinkurt)	47 GUAYA (Vetch)	63 SHIRO/KOLLO		
16 COFFEE	32 SPINACH (Quosta)	48 NUEG	64 BUTTER/CHEESE		

Code (f) QUANTITY UNITS

1 KILOGRAMMES	11 BOBO	21 GAN	40 BIG MADABERIA	50 BUNCH (BANANAS)	60 EGIR
2 QUINTAL	12 PACKETS	22 ENSIRA	41 SMALL MADABERIA	51 MELEKIA/LIK	61 WESLA
3 CHINET	13 BAGS	23 GURZIGNE	42 DIRIB	52 GUCHIYE	62 MESFERIA
4 DAWLA	14 BUNDLES	24 TASSA	43 SAHIN/LOTERY	53 BEKOLE	63 KURFO
5 KUNNA	15 PIECES	25 KUBAYA/KELASA	44 MANKORKORIA	54 ENKIB	64 KOLELA
6 MEDEB	16 BARS	26 BIRCHIKO	45 PLATIC BAG/FESTAL	55 SHEKIM	
7 KURBETS	17 BOXES	27 SINI	46 ZURBA	56 NUMBER	95 OTHER (Specify)
8 SILICHA	18 LEAVES	28 GEMBO	47 AKARA	57 GOTERA	
9 AKMADA	19 LITRES	29 BOTTLES	48 SMALL PLASTIC BAG (MIKA)	58 LEMBA	
10 ESIR	20 KIL	30 BIRR	49 KERCHAT/KEMBA	59 SHIRIMERI	

Code (g):Type of Work Sharing Party (PLEASE USE LOCAL NAME)
1 WONFEL
2 DABBO
3 JIGGI
4 GEAZE
5 YETSCHSQUASHA
6 CHINNET
7 WABERA
8 KEBBO
9 OTHER _____________ SPECIFY

Code (c) Method of Payment	**Code (d) Type of Fertilizer**	**Code (e) Location of sale?**	**Code (f) Land Units**	
1 CASH (or largely cash)	1 DAP	1 THIS VILLAGE	1 GASHA	13 TINTO
2 LOAN FROM PROVIDER	2 UREA	2 ANOTHER VILLAGE	2 HECTARE	14 ERMIJA
3 PAYMENT IN KIND	3 DAP + UREA	3 LOCAL MARKET TOWN	3 GEMED	15 DERO
4 BY PROVIDING LABOUR	4 OTHER___________	4 REGIONAL CENTER	4 TIMAD	16 GEZEM
5 NO PAYMENT		5 ADDIS ABABA	5 KERT	17KEND
6 OTHER_____________		6 OTHER (SPECIFY)	6 MASSA	18 SQUARE ZHIR
7 CASH AND IN KIND			7 KEDEMA	19 MEDEB
			8 KUFARO	20 SQUARE METER
			9 ZHIR	22 BOY
			10 OTHER_	

Code (h): Purpose of Work Party
1 PLOUGHING/DIGGING/LAND PREPARATION FOR MEHER
2 WEEDING/WATERING/PRUNING FOR MEHER
3 HARVESTING FOR MEHER
4 TRESHING/STORAGE/PROCESSING FOR MEHER
5 CONSTRUCTION
6 PLOUGHING/DIGGING/LAND PREPARATION FOR BELG
7 WEEDING/WATERING/PRUNING FOR BELG
8 HARVESTING FOR BELG
9 TRESHING/STORAGE/PROCESSING FOR BELG
10 OTHER (SPECIFY)

PART II, SECTION 2A: AGRICULTURAL INPUTS - LABOUR SHARING

Since the beginning of the last (finished) Meher season [OR RELEVANT MAIN SEASON], did you or any other member of your household call for a work party [debbo, wenfel,...] for your household? **YES 1** **NO 2**	IF YES, **GO TO Q3**.
	IF NO, **GO TO next section**

3. FOR EACH TIME YOU CALLED A WORK PARTY, PLEASE GIVE SOME DETAILS

	4. Type of work group **(code g)**	5. Type of task of work party was called for? **(code h)**	8. On which plots did you use a working party? **Copy numbers from part II, section 1**			10. How many people participated in this work party? **Males**	**Females**	11. How many members of your own household were involved? **Males**	**Females**	12. For how many days was the working party active for?
1										
2										
3										
4										
5										

PART II, SECTION 2B: AGRICULTURAL INPUTS – FAMILY AND HIRED LABOUR

We want to know about labour input on temporary growing crops (NOT PERMANENT CROPS) during the MOST RECENT COMPLETED MEHER SEASON. Please exclude labour provided via labour sharing groups.

	Excluding labour sharing, that is, apart from working with a work group, were any members of your household involved on your own land (including the head)?					Did you hire in any labour from outside the household to work on your own land?						Total payment in kind: sum of all payments in kind to all workers.		
	1 YES…1 NO…..2 IF NO, Q6	2A How many adult household members involved?	3B How many days IN TOTAL was worked by adults in your household?	4A How many children household members? (SKIP TO Q6 if 0)	5B How many days IN TOTAL was worked by children in your household?	6 Number of people involved? (if none, write 0)	7 On which plots did you employ hired labour?**Copy numbers from Part II, Section 1A**			8 TOTAL number of days worked	9 Total payment (total of cash payments)	10 Crop code: **Code (a)**	11 amount	12 Quantity unit: **Code (b)**
Planting and land preparation														
General cultivation (incl. weeding, watering, pruning)														
Harvesting (incl. basic processing for sale, storage)														

13. Was your output affected because someone in the family was too ill at critical periods of the farm operation? **YES 1** **NO 2**	
14. Was your output affected because outside labour was not available at the right time? **YES 1** **NO 2**	
15. Was your output affected because oxen were not available at the right time? **YES 1** **NO 2**	
16. Was your output affected because you could not get fertiliser at the right time? **YES 1** **NO 2**	

PART II, SECTION 2C: AGRICULTURAL INPUTS: OTHER EXPENDITURES

We would like to ask you some questions about expenses related to inputs into crop agriculture during the last completed Meher season and the preceding Belg. For **permanent crops**, if there is only one harvest, give the total expenditure of each item for the last harvest in the table related to 'Meher'. If there are two harvests per year for the permanent crop, give first the costs related to the largest harvest in the 'Meher' table and then those related to the second harvest in the next box. If more than two harvests take place or if the crop is harvested continuously throughout the year, give the total expenses on inputs for the last 12 months in the 'Meher' table.

During the LAST (completed) MEHER, has the household incurred any expenses related to inputs for crop agriculture, including for the hiring of labour?

1 Type of expenditure during MEHER or on permanent crops	2 Method of payment **code (c)**	3 Where did you buy the input? **code (e)**	4 Total payment in cash (BIRR)	5 If payment in kind, give total payment in kind. crop **code (a)**	amount	unit **code (b)**	6 [FERTILISER ONLY] How much did you use IN KILOGRAMS during the last MEHER season and on which main crops? TYPE **code (d)**	CROP 1 **code (a)**	TYPE **code (d)**	CROP 2 **code (a)**
Fertilizer										
Pesticides (incl. fungicides and herbicides)										
Seeds and young plants (chigegn)										
Labour for crop production										
Transport related to crop production and crop sale										
Rent for oxen										
Tractor, harvester, or combine services										
Other _____________________ (specify)										

PART II, SECTION 2C: AGRICULTURAL INPUTS: OTHER EXPENDITURES Continued ….

During the LAST (completed) BELG, has the household incurred any expenses related to inputs for crop agriculture, including for the hiring of labour? Please give details.

7 Type of expenditure during BELG	8 Method of payment **code (c)**	9 Where did you buy the input? **code (e)**	9 Total payment in cash (BIRR)	10 If payment in kind, give total payment in kind.			11 [FERTILISER] How much did you use IN KILOGRAMS during the last Belg season and on which main crops?			
				crop **code (a)**	amount	unit **code (b)**	TYPE **code (d)**	CROP 1 **code (a)**	TYPE **code (d)**	CROP 2 **code (a)**
Fertiliser										
Pesticides (incl. fungicides and herbicides)										
Seeds and young plants (chigegn)										
Labour for crop production										
Transport related to crop production and crop sale										
Rent for oxen										
Tractor, harvester, or combine services										
Other _____________________ (specify)										

12. For [FERTILISERS, PESTICIDES, IMPROVED SEED, OUTPUT OBTAIND and LABOUR COSTS] how much did you use IN KILOGRAMS or LITRES during the last Meher Season And Belg season and on which main crops? ***In particular starting from cereal crops*** *(White and Black/Mixed Teff, Barley, Wheat, Maize, Sorghum, Millet /Zengada, Oats/Aja,)*

Cropped Plot Size (**copy from part II section 1A**)			**Season:** 1. Meher 2. Belg	**Crop**:	Fertilizer used			Seed used IN KILOGRAMS		Chemicals/herbicides/ Pesticides used		How much output of the [..]..crop obtained? (Amount in KGs)	Machinery service used (Tractor or Combiner) In Hrs used	Total payment in(Birr) for Labour use	Total payment (in Birr) for Oxen Rent	Total payment (in Birr) for Transport related (during production and crop sale)
Plot No.	Area	Unit **Code(f)**		**Code (a)**	TYPE **Code (d)**	Amount IN KGs	Expense for it in Birr	Local	Improved	Amount IN LRs	Expense for it in Birr					

CODES FOR PART II, SECTION 3: AGRICULTURAL PRACTICES AND TECHNOLOGY

	Code (a) : Type of Soil Conservation Measure
1	STONE BUNDS INDIGENOUS
2	SOIL BUNDS INDIGENOUS
3	STONE BUNDS INTRODUCED
4	SOIL BUNDS INTRODUCED
5	FANYA JUU
6	CONTOUR PLOUGHING
7	STRIP CONNING
8	ALLEY CROPPING (SESBANIA)
9	FANYA CHINI
10	SOIL BUNDS (PLANTED WITH SESBUNIA)
11	OTHER

	Code (b) Reasons for No Conservation
1	NO NEED/ NO EROSION PROBLEM
2	SHORTAGE OF LABOUR
3	HAVE DOUBTS ABOUT EFFECTIVENESS OF METHODS OF CONSERVATION
4	DON'T KNOW WHAT TO DO
5	NO SKILLS TO IMPLEMENT MEASURES
6	OTHER ________________

	Code (c) Main Problems Fertilizer System
1	SHORTAGE OF SUPPLY
2	LATE ARRIVAL
3	HIGH PRICE
4	LACK OF CREDIT
5	NOT RELEVANT FOR ME
6	OTHERS ________________

	Code (d) Climate Adaptation Technologies		
1	SOLD LIVESTOCK	11	CHANGING PLANTING DATES (PLANTING EARLY)
2	PLANTING TREES	12	CHANGING PLANTING DATES (PLANTING LATE)
3	USING CROP ROTATION AND DIVERSIFICATION	13	INCREASED USE OF INTERMEDIATE AND CATCH-UP CROPS
4	USING SOIL CONSERVATION	14	DIVERSIFYING FROM FARM TO NONFARM ACTIVITIES
5	INCREASED HARVEST OF WATER	15	USING MIXED FARMING SYSTEM (CROP&LIVESTOCK)
6	MIGRATING TO OTHER AREA	16	
7	IMPROVING CROP RESIDUES MANAGEMENT FOR LIVESTOCK FEED	17	USING MORE FERTILIZERS, INSECTICIDES & PESTICIDES
8	USING IRRIGATION	18	USING LEGUMES IN CROP ROTATIONS
9	USING ADAPTIVE QUALITY SEEDS	19	USE SOIL MANAGEMENT PRACTICES THAT REDUCE FERTILIZER USE
10	CROPPING DIFFERENT CROP VARIETIES	20	CHANGING FARMING SYSTEM FROM CROP TO LIVESTOCK OR VICE VERSA.

PART II, SECTION 3: AGRICULTURAL PRACTICES AND TECHNOLOGY

1. Is there any irrigation on any of your plots? **YES….1** **NO….2** **If yes, how much area (approximate) is under irrigation:- see Code (f) Land units page on 12:**	Area:	**Land units:**
2. Do you use manure on your fields? **YES….1** **NO….2**		
3. Do you practice any soil conservation measure on any of your land? **YES….1 NO….2** **IF NO, GO TO Q5**		
4. If yes, which type? **Code (a)**		
5. If no, why not? **Code (b)**		
6. Has any of your land been under the government's extension program in the last 5 years? **YES….1** **NO….2**(IF NO, GO TO Q8)		
7a.Do you have access to information on climate or weather variation **YES….1** **NO….2**		
7b. Have you noticed changes in mean temperature and rainfall over the past two decades **YES….1** **NO….2**		
7c.How are you adapting to climate change **OR** which type of adaptation Technologies are using? (***multiple response is possible***) **Code (d)**		
8. How many times were you visited by an extension agent during the last main season?		
9. Have you used fertiliser in any of the last five year? **YES….1 NO….2** **IF NO, GO TO Q12**		
11. When you last used fertiliser in the last five years, did you get fertiliser on credit? **YES….1** **NO….2**		
12. What (if any) are the main problems with the fertiliser supply system (most important problem first) -up to three responses **Code (c)**		
13. Are you involved in any water harvesting? **YES….1** **NO….2**		

CODES FOR PART II, SECTION 4: LIVESTOCK OWNERSHIP; SECTION 5: LIVESTOCK EXPENDITURE AND INCOMEand SECTION 6: EVENTS DURING THE LAST KIREMT SEASON

	Code (a) Type of Livestock
1	CALVES
2	BULLS
3	OXEN
4	HEIFER
5	COWS
6	SHEEP
7	GOATS
8	HORSES
9	DONKEYS
10	MULES
11	CAMELS
12	YOUNG BULLS
13	CROSS BREED COW
14	CROSS BREED BULL.
15	CROSS BREED OX
16	CROSS BREED YOUNG BULL
17	CROSS BREED HEIFER
18	CROSS BREED CALVES.
19	EXOTIC OR FRESIAN COWS
20	CHICKEN or POULTRY
21	EXOTIC OR FRESIAN HEIFER
22	EXOTIC OR FRESIAN YOUNG BULL.
23	BEE HIVES
24	OTHERS (IF ANY)_______________

	Code (b) Location of Sale or Purchase?
1	THIS VILLAGE
2	ANOTHER VILLAGE
3	LOCAL MARKET TOWN
4	REGIONAL CENTER
5	ADDIS ABABA
6	OTHER (SPECIFY)

	Code (c) Method of Payment
1	CASH (or largely cash)
2	LOAN FROM PROVIDER
3	PAYMENT IN KIND
4	BY PROVIDING LABOUR
5	NO PAYMENT
6	OTHER_____________
7	CASH AND IN KIND

	Code (e) Crop Codes		
1	WHITE TEFF	32	SPINACH (Quosta)
2	BLACK/MIXED TEFF	33	GARLIC (Nech Shinkurt)
3	BARLEY (Gebis)	34	YAM
4	WHEAT (Durrah, Sinde)	35	FASOLIA
5	MAIZE (Bekolo/Bahirmashla)	36	FRUIT
6	SORGHUM / Mashila	37	MANGO
7	ZENGADA	38	KOCHO
8	OATS	39	HAMICHO
9	HORSE BEANS (Bakela)	40	CHICK PEAS (Shimbra)
10	LINSEED (Telba)	41	COW PEAS (Ater)
11	GROUNDNUTS (Lew)	42	ORANGE
12	SESAME (Selit)	43	GODERE
13	BLACK PEPPER (Kundoberbere)	44	ADENGUARE
14	LENTILS (Mesir)	45	SWEET POTATOES (SekuarDinich)
15	VEGETABLES	46	TOMATO
16	COFFEE	47	GUAYA (Vetch)
17	CHAT	48	NUEG
18	ENSET	49	CABBAGE (Gomen)
19	BANANAS	50	PADDY, RICE
20	GRASS	51	SINAR/GERIMA
21	GESHO	52	HARICOT BEANS (Boloke)
22	EUCALYPTUS	53	FIELD PEAS
23	SHIEFERA/HALEKO	54	FENUGREEK (Abish)
24	DAGUSSA	55	BEET ROOT (Key Sir)
25	SUNFLOWER	56	CARROT
26	POTATOES	57	GINGER (Jinjibel)
27	SUGARCANE	58	SELATA (Lettuce)
28	TOBACCO	59	TIKL GOMMEN
29	PINEAPPLE (Ananas)	60	PUMPKIN (Duba)
30	AVOCADO	95	OTHER
31	ONIONS (Shinkurt)		

Code (d) QUANTITY UNITS

1 KILOGRAMMES	11 BOBO	21 GAN	40 BIG MADABERIA	50 BUNCH (BANANAS)	60 EGIR
2 QUINTAL	12 PACKETS	22 ENSIRA	41 SMALL MADABERIA	51 MELEKIA/LIK	61 WESLA
3 CHINET	13 BAGS	23 GURZIGNE	42 DIRIB	52 GUCHIYE	62 MESFERIA
4 DAWLA	14 BUNDLES	24 TASSA	43 SAHIN/LOTERY	53 BEKOLE	63 KURFO
5 KUNNA	15 PIECES	25 KUBAYA/KELASA	44 MANKORKORIA	54 ENKIB	64 KOLELA
6 MEDEB	16 BARS	26 BIRCHIKO	45 PLATIC BAG/FESTAL	55 SHEKIM	
7 KURBETS	17 BOXES	27 SINI	46 ZURBA	56 NUMBER	95 OTHER (Specify)
8 SILICHA	18 LEAVES	28 GEMBO	47 AKARA	57 GOTERA	
9 AKMADA	19 LITRES	29 BOTTLES	48 SMALL PLASTIC BAG (MIKA)	58 LEMBA	
10 ESIR	20 KIL	30 BIRR	49 KERCHAT/KEMBA	59 SHIRIMERI	

PART II, SECTION 4: LIVESTOCK OWNERSHIP
Can you tell us about your herd of livestock at present?

Type of Livestock (a) **IF CROSS-BREEDS, USE CODES ABOVE!**	1 Number owned and present at your farm	2 If you would sell one of the... [..].. today, how much would you receive from the sale? BIRR
CALVES....01		
BULLS.....02		
OXEN......03		
HEIFER....04		
COWS......05		
SHEEP.....06		
GOATS.....07		
HORSES....08		
DONKEYS...09		
MULES.....10		
CAMELS....11		
YOUNG BULLS...12		

PART II, SECTION 5: LIVESTOCK EXPENDITURE AND INCOME
IN THE LAST 12 (13 Ethiopian) months, have you had any of the following expenditures related to livestock?

Type of expenditure	CODE	Method of payment **Code (c)**	2 Where did you purchase or get the input? **Code (b)**	3 Cash value (if in kind, give estimated cash value)
Labour for herding	1			
Feed	2			
Veterinary services/medicine	3			
Other expenses	4			

PART II, SECTION 5: LIVESTOCK EXPENDITURE and INCOME Continued …

What was your gross income from the sale of household's animal products IN THE LAST 12 (13 Ethiopian) months?

Type	CODE	4 Did you sell any ..[..]..? YES...1 NO....2 ➢NEXT TYPE	5 Amount sold?	6 Unit **code (d)**	7 Total revenue obtained from the sale of ..[..]..	8. Where did you sale the product? **Code (b)**
Meat (EXCLUDE LIVE ANIMALS)	69					
Hides/skins	63					
Butter/cheese	64					
Milk/cream	65					
Dung cakes	66					
Chicken	67					
Eggs	68					

PART II, SECTION 6: EVENTS DURING THE LAST KIREMT SEASON

Please think back at the last main rainy season (Kiremt). We would like to know whether any of the following events happened to you which affected the growth of your crops and the harvest. These questions should be asked to all farmers who harvest during the Meher season, AND ALL FARMERS WHO GROW PERMANENT CROPS; and any other farmers for whom these rains can be relevant.

Permanent crop growers should be asked in general about the growing season preceding the last main harvest. If the crop is continuously harvested, ask for a general assessment of the last growing season. When referring to 'Kiremt', interpret this for the permanent crop growers as the main rains. Space is provided to qualify answers if needed.

	Codes			COMMENTS
1. Are the Kiremt rains important for your crops?	YES 1	NOT VERY IMPORTANT 2	NO **3** (If NO, GO TO Q7)	
2. According to your own plans, did the first Kiremt rains come on time?	ON TIME 1	TOO LATE 2	TOO EARLY 3	
3. Was there enough rain on your fields AT THE BEGINNING of the rainy season?	ENOUGH 1	TOO MUCH 2	TOO LITTLE 3	
4. Was there enough rain on your fields DURING the growing season?	ENOUGH 1	TOO MUCH 2	TOO LITTLE 3	
5. Did the rains STOP on time on your fields?	ON TIME 1	STOPPED TOO LATE 2	STOPPED TOO EARLY **3**	
6. Did it rain near the harvest time?	YES 1	NO 2		

7. Did any of your crops suffer from any of the following factors? YES.........1 NO..........2

Low temperatures	Wind/storm	Flooding/water logging	Plant diseases	Insects	Livestock (eating/trampling crops)	Birds/other animals	Weed damage

8. Please mention the crops which were most affected by the weather, by insects, animals or pests during the last Meher & Belg season (or equivalent period), and mention whether they were Moderately or very badly affected. **(up to three). Give comments if necessary.** For permanent crops, if there are two growing seasons, refer to the less important one, since the main one ought to be referred to in the previous section.

Season Code:**1. Meher 2.Belg**	CROP **code (e)**	HOW AFFECTED: ***MODERATELY.....1 SEVERELY.......2***	COMMENTS

PART III: FOOD CONSUMPTION and HEALTH
The respondent for this part of the questionnaire (PART III) should be a Female member of the household who knows about the food consumed and purchased. If the household head is male, the mother of his children would be most appropriate.

PART III: CONTAINS *four SECTIONs*:

SECTION 1: HOUSEHOLD CONSUMABLES
SECTION 2: CONSUMPTION HABITS
SECTION 3: FOOD EXPENDITURE AND CONSUMPTION
SECTION 4: WATER AND HYGIENE

CODES FOR PART III: FOR SECTION 1, SECTION 2andSECTION 3

b) Codes for Quantity Units

1 KILOGRAMMES	11 BOBO	21 GAN	40 BIG MADABERIA			**(c) CODES FOR GIFT/LOAN/PAYMENT IN KIND**		**Code (d), Months**	
2 QUINTAL	12 PACKETS	22 ENSIRA	41 SMALL MADABERIA	52 GUCHIYE		1 FAMILY, LOCAL			
3 CHINET	13 BAGS	23 GURZIGNE	42 DIRIB	53 BEKOLE		2 FAMILY, NON-LOCAL		1 MESKEREM	8 MIAZIA
4 DAWLA	14 BUNDLES	24 TASSA	43 SAHIN/LOTERY	54 ENKIB		3 NEIGHBOR/VILLAGE MEMBER		2 TIKMIT	9 GUENBOT
5 KUNNA	15 PIECES	25 KUBAYA/KELASA	44 MANKORKORIA	55 SHEKIM		4 INDIVIDUAL FROM OUTSIDE VILLAGE		3 HIDAR	10 SENE
6 MEDEB	16 BARS	26 BIRCHIKO	45 PLATIC BAG/FESTAL	56 NUMBER		5 GIFT FROM GOVERNMENT		4 TAHSAS	11 HAMLE
7 KURBETS	17 BOXES	27 SINI	46 ZURBA	57 GOTERA		6 GIFT FROM AID AGENCY, NON-GOV'T		5 TIR	12 NAHASSIE
8 SILICHA	18 LEAVES	28 GEMBO	47 AKARA	58 LEMBA		7 FOOD-FOR-WORK		6 YEKATIT	13 PAGUME
9 AKMADA	19 LITRES	29 BOTTLES	48 SMALL PLASTIC BAG (MIKA)	59 SHIRIMERI		8 WAGES IN KIND		7 MEGABIT	
10 ESIR	20 KIL	30 BIRR	49 KERCHAT/KEMBA			9 BARTER			
60 EGIR	62 MESFERIA	64 KOLELA	50 BUNCH (BANANAS)			10 LOAN			
61 WESLA	63 KURFO	95 OTHER (Specify)	51 MELEKIA/LIK			11 OTHER (SPECIFY)			

PART III, SECTION 1: HOUSEHOLD CONSUMABLES.
1. Did the household purchase any of the following **for its own consumption during the last MONTH? If so, where did you purchase these?**

Commodity	**Code**	**Total Expenditure (BIRR)**	**Where purchased (Code e)**		**Code (e), Where purchased**
Matches	310				1 THIS VILLAGE
Batteries	311				2 ANOTHER VILLAGE
Candles (tua'af), incense	312				3 LOCAL MARKET TOWN
Laundry soap/OMO/endod/besana leaves	320				4 REGIONAL CENTER
Hand soap	321				5 ADDIS ABABA
Other personal care goods (incl.sendel,matent,..)	322				6 OTHER (SPECIFY)
Charcoal	301				
Firewood	302				
Kerosene	303				

PART III, SECTION 3: FOOD EXPENDITURE AND CONSUMPTION

1. We would like to ask you about all the food that was bought for consumption or was consumed from your own (BETESEB's) stock, IN THE LAST WEEK.

In last week, did your household consume any of the following? If othercrops were bought for consumption or were consumed, choose and write from any CROP CODES in the questionnaire.

Food type or Crops Consumed	**Code (a)**	How much was purchased? How much was spent?			Did you consume this food from your own harvest or your own stock? How much?		Did you receive this food as a GIFT, a LOAN, as WAGE IN KIND or as BARTER? How much? Who gave you this food? GIVE AMOUNT **CONSUMED** IN THE LAST WEEK		
		Amount	**Unit Code (b)**	**Total Expenditure (Birr)**	**Amount**	**Unit Code (b)**	**Amount**	**Unit Code (b)**	**Source Code (c)**
Teff	1								
Barley (Gebis)	3								
Wheat/ Durahh (Sinde)	4								
Maize (Bekolo/Bahismashla)	5								
Sorghum (Mashila; Dagusa)	6								
Millet (Zengada)	7								
Lentils (Misir)	14								
Horse Beans (Bakela)	9								
Cow Peas (Ater)	41								
Chick Peas (Shimbra)	40								
Milk/Yoghourt (Ergo)	65								
Beef (YekebitSiga)	61								
Mutton (Yebeg)/Goat Meat(YefiyelSiga)	62								
Chicken	67								
Eggs	68								
Butter/Cheese	64								
Tella/Tej	71								
Birra (Bottled)	72								
Chat	17								
Araqi/Kathikala	73								
Soft Drinks	74								
Coffee	16								
Sugar	75								
Salt	81								
Cooking Oil	82								
Spices/Karia/Berbere	83								
Bread (Dabo)	84								
Macaroni/Spaghetti	85								
Potatoes	26								
Enset	18								
Sweet Potatoes	45								
Green Leaf Vegetables	15								

PART III, SECTION 3: FOOD EXPENDITURE AND CONSUMPTION, *CONTINUED*

3. Generally, where do you purchase food grains? **(Code e)**	
4. Generally, where do you purchase fruits or vegetables? **(Code e)**	
5. Generally, where do you purchase meat and/or dairy products? **(Code e)**	
6. Generally, where do you purchase sugar, salt and/or cooking oil? **(Code e)**	
7. Generally, where do you purchase processed foods such as sodas, other beverages or packaged food such as biscuits? **(Code e)**	
8. Has the household purchased any prepared foods, or paid to eat food outside the household in the last week? **(1 YES 2 NO)** ***(If no, skip to Q10.)***	
9. What was the total expenditure on prepared foods and food eaten outside the household **in the last week? (BIRR)**	
10. IN THE LAST FOUR MONTHS, has the household purchased any cereals or pulses in large quantities, i.e. More than 50 kg (1/2 quintal) in one purchase? (EXCLUDING BULK PURCHASES IN THE LAST WEEK WHICH WERE PREVIOUSLY MENTIONED.**(1 YES 2 NO)**	

PART III: SECTION 2: CONSUMPTION HABITS

1. How many months in the last 12 (13 Ethiopian) months did you have problems satisfying the food needs of the household?							
2. During the last rainy season, did your household suffer any shortage of food to eat? **YES.................1 NO..................2**							
3. Thinking back over the last 12 (13 Ethiopian) months, in which month was the shortage of food most acute for your household? **(Code d)** (*If household did not experience any food shortage, skip to 6.)*							
2. Compared to your usual diet, did you eat foods that you ordinarily would not eat, "less preferred foods**"? YES............1 NO...............2**							
3. Compared to your usual diet, did you cut back quantities served per meal to adult males? **(Code d)**							
4. Compared to your usual diet, did you cut back quantities served per meal to adult females? **(Code d)**							
5. Compared to your usual diet, did you cut back quantities served per meal to boys **(Code d)**							
6. Compared to your usual diet, did you cut back quantities served per meal to girls **(Code d)**							
7a. During the worst month, how many times a day did adults in your household eat?							
7b. During the worst month, how many times a day did children in your household eat?							
8a. During a good month, how many times a day did adults in your household eat?							
8b. During a good month, how many times a day did children in your household eat?							
9. Are there any months in a **typical year** when the household runs out of home-grown food and therefore has to buy food, ask for gifts or has less to eat than otherwise? [WE ARE INTERESTED IN SEASONAL PROBLEMS, NOT EXCEPTIONAL YEARS; THE ISSUE IS TO KNOW WHEN STOCKS TYPICALLY GET DEPLETED.] Give the months in a typical year it usually happens. **Code (d)**							
10. Did this happen **during the last 12** (13 Ethiopian) **months?** Give the months during which it happened? **Code (d)**							

CODES FOR PART III, SECTION 4: WATER AND HYGIENE

Code (a), Toilets		Code (b), Garbage disposal		Code (c), Sweep compound		Code (d), Source of drinking water
1 Flush toilet shared		1 Household dumps at will		1 Once a day		1 Pond or dam
2 Flush toilet private		2 Burned		2 More than once a day		2 Stream or river
3 Pit latrine shared		3 Used as green manure		3 Less than once a day		3 Spring
4 Pit latrine private		4 Buried		4 Never		4 Well
5 Pan/bucket		5 Periodically collected from Household				5 Borehole
6 No toilet		6 Periodically collected from specified dumping point				6 Rainwater
						7 Piped water (not in house)
						10 Other

PART III, SECTION 4: WATER AND HYGIENE
We would like to learn about hygiene practices in your household.

1. What form of toilet do you own? **(Code a)**	
2. How is garbage disposed of? **(Code b)**	
3. How often is the compound swept? **(Code c)**	
4. What is your main source of drinking water? (Code d)	
5. How long does it take to get there/source of drinking water? (Lemehed bicha)?	(minutes)
6. How long does it take you to get to the place where you normally collect fuel?	(minutes)

CONFIRMATION*: BY THE RESPONDENT*

I hereby confirm that these responses are true and honesty responses of mine.

Name of the Household's Head or Respondent: ________________ **Place:** ________________

Date: ________________ **Signature:** ________________

---*THE END!!!!*---

THANK YOU FOR YOUR GENUINE, UNRESERVED, VALUABLE RESPONSES AND TIME.