ADDIS ABABA UNIVERSITY
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PhD in Development Studies, Research

Agricultural Input Use, Total Factor Productivity Growth and Rural Poverty: Dynamics and Patterns in Southern Ethiopia

By:

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DECLARATION

This is to certify that the Ph.D. dissertation research prepared by **MERIHUN FIKRU** which is titled: **"Agricultural Input Use, Total Factor Productivity Growth and Rural Poverty: Dynamics and Patterns in Southern Ethiopia",** submitted in partial fulfillment of the requirement for the Doctor of philosophy in Development Studies (Rural Development Studies) complies with the regulation of the university and meets the accepted standard with respect to originality and quality.

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DECLARATION

I, Merihun Fikru, herewith declare that this thesis entitled "**Agricultural Input Use, Total Factor Productivity Growth and Rural Poverty: Dynamics and Patterns in Southern Ethiopia**" is the product of my original research work. It is a dissertation that has been submitted to the Center of Rural Development Studies, College of Development Studies, Addis Ababa University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Development Studies. I solemnly declare that I have undertaken the research work independently with the guidance and support of my advisors 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.

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Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

AIC	Akaike's information criterion
AGR	Average Growth Rate
AgSS	Agricultural Sample Survey
ATE	Average Treatment Effect
ATENT	Average Treatment Effect Not Treated
ATET	Average Treatment Effect Treated
BIC	Bayesian information criterion
CF	conversion factors
CSA	Central Statistics Authority
CPCPH	Consumption per capita per household
DAs	Development Agents
DEA	Data Envelopment Analysis
DRF	Dose Response Function
EAs	Enumeration Areas
EET	Exogenous and Endogenous Treatment
ESS	Ethiopian Socio-economics Survey
FGD	Focus Group Discussion
FGT	Foster J Greer J and Thorbecke
GTP-I	The First Growth and Transformation Plan
H_0	null hypothesis
Ha	Hectares
HCI	Head Count Index
IFPRI	International Food Policy Research Institute
JDAs	The Journal of Developing Areas
KH-Model	Kumbhakar and Heshmati (1995) model
KLH	Kumbhakar-Lien-Hardaker
KII	Key Informant Interviews
LSMS	Living Standard Measurement Survey

LDCs	Less Developed Countries
MDPI	Multidisciplinary Digital Publishing Institute
MLE	Maximum Likelihood Estimations
NEPAD	New Partnership for Africa's Development
NSFA	Non-Stochastic Frontier Analysis
PDC	Planning and Development Commission
PSM	Propensity Score Matching
RCEPC	Real Consumption Expenditure per Capita
SFA	Stochastic Frontier Analysis
SF	Stochastic Frontier
SNNPR	Southern Nations, Nationalities, People's Region
SPF	Stochastic Production Frontier
SSA	Sub-Saharan Africa
TC	Technical change
TEC	Technical efficiency
TELC	Technological change
TFE	True Fixed Effect
TFP	Total Factor Productivity
TLUs	Tropical livestock units
TVIDM	Time-varying Inefficiency Decay Model

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

Farming system dynamism is an engine of improving agricultural productivity and reducing rural poverty. However, due to variability of input use and mechanization, the growth rate is different from area to area and household to household (Alemu and Zewdie, 2015; World Bank, 2019). Resistance to adopting new technologies significantly affects the level of total factor productivity (TFP) growth. There is also poor practice in recording the sources of growth as well as identifying chronic and time-varying inefficiencies. Besides, the recommendations about the real sources of TFP based on farm size are unclear (David, 2012; Balié and Ghins, 2017).

Moreover, inefficiency into time-varying and time in-varying inefficiencies occur due to occasional events and differences in adopting technologies, respectively. Among many, the determinant factors of productivity growth: adoption of inputs, improving efficiency, cultivable land expansion, and intensification. The incompatible development policy of productivity in Ethiopia is insignificant on the existing facts of producers and agro-ecology (Brink et al., 2009). However, studies conducted at the regional level using panel data are rather scanty. Therefore, this study seeks to contribute to the limited knowledge about the dynamics of agricultural TFP growth in technical efficiency (TE) and technical change (TC) at the regional level using panel data (Rashid *et al.,* 2013; Sheahan, 2014; Nauges, 2017).

Agricultural TFP for Sub-Saharan Africa (SSA) through crop outputs and inputs (land, labor, capital and technology) are derived from the ratio of output and aggregate inputs. Major agricultural inputs are, land (total crop area harvested), labor (number of economically active adults), livestock capital (total number of animals, in cattle-equivalents), technologies (tractors in use, various agronomical practices), and intermediate inputs (fertilizer, improved seed and chemical). The TFP of crops is a portion that is not explained by a number of inputs in the production process. Therefore, intensity depends on agricultural inputs is considered as the characteristic of past and current performance of crop productivity (Kumbhakar *et al.,* 2015; Godin, 2015).

Adoption and diffusion of agricultural input is considered as one of the basic mechanisms in which crop productivity and economic growth can be improved in developing countries. Those mechanisms to encourage adoption of better farming technologies broadly defined as improved agricultural practices, inputs, crop varieties, and others like crop insurance or innovative lending products which increase productivity. This is particularly relevant for many SSA where the agricultural sector is dominant and characterized by low productivity (Rashid, Tefera et al., 2013, Sheahan 2014).

Poverty is a multidimensional concept with several definitions and measures in its analysis. Despite the lack of consensus in the definition and concept of poverty, the term 'poverty' is the one that has vastly used and studied. In spite of this fact, the welfarist and non-welfarist approaches are the two most widely used in the conceptualization and assessment of well-being in poverty analysis? Rural poverty due to low crop productivity growth has been a long-standing challenge with uneven progress across Africa (Deaton, 2016). To reduce rural poverty and narrow productivity growth gaps over time, enhancing TFP growth through bringing substantial improvements in efficiency and increasing technology adoption of crops are mandatory (Dercon *et al.,* 2005; Duclos, 2010; Christiaensen, 2011; Porter, 2012).

1.2.Statement of the Problem

Globally, agriculture input transition from traditional to mechanized form is associated with the shift in the farming system. Thus, agricultural input use is recognized as a stimulant for raising TFP and reducing poverty in the world. However, the rate of a shift in the farming system differs from country to country. Comparatively, less developed countries (LDCs) faced problems in making the sector more mechanized and productive (Bachewe *et al.,* 2015; Minot and Daniel, 2005). Though Boserup (2007) suggested improved inputs, technology, and best agronomic practice can determine the growth of agriculture, there is difficulty in applying those techniques that can enhance the productivity growth in most of the LDCs crops (Sime, 2015; Guan *et al.,* 2015).

Moreover, on average the national TFP of grain crops in aggregate was 7.23 in the last two decades (CSA, 2016). However, the average TFP level by crop: barley (1.4), maize (2.1), sorghum (1.7), teff (1.2), wheat (1.6) in southern Ethiopia (CSA, 2016). The land covered by teff[1](24%), maize(16.98%), sorghum (14.97%), and wheat (13.49%) of the total grain cultivation, 87% was produced by these crops in Ethiopia (McGuire, 2015; Abafita et al., 2016; Sandhu, 2019). Cereals contributed 87.42% of the grain production. Maize, teff, wheat and sorghum made up 27.02%, 17.29%, 15.63%, and 16.36% of the grain production, in the same order (McGuire, 2015; Abafita et al., 2016; Sandhu, 2019). Comparatively, the productivity of these crops in SNNPR was below the national level average except for maize in the last two decades. In the 20th Era, those intermediary inputs (fertilizer, seeds and chemical) are considered as the determinant factors that can affect productivity of crops. Crop TFP is defined as how efficiently inputs of agricultural production are utilized. However, TE and TC are components of TFP remained an area of research in LDCs (IFAD, 2016; Balié and Ghins, 2017).

Lack of proper recoding of sources of growth and ambiguity in of factor of production like land are swamp challenges in SSA crop production process (IFDC, 2012; Teklewold, 2013; Seaward, 2016; Jorgenson, 2018).

On the other hand, previous studies based on cross-sectional data and SF approach measured at the various local levels (Gollin, 2010; Ndulo, 2011; Kathuria, 2013; Abafita et al., 2016). Therefore, research with panel data and SF approach fulfills the knowledge gap in the field. While TFP measurement is most appropriate to analyze dynamics of TFP; the vast majority of statistical analysis has been conducted using partial factor productivity in Ethiopia (Kitila et al, 2014; Ajadi et al., 2017).

Furthermore, less adoption for new agricultural inputs is also a mega-scale reason for less crop productivity and aggravating poverty in rural Ethiopia. Poor infrastructure, limited access to credit for smallholders, fewer export crops, inadequate access to input and output markets are also the main constraints that hinder crop productivity (Davidson *et al.,* 2013; Alemu, 2015). Despite lower returns to crop production, smallholder subsistence farmers continue to prioritize crop production for the market in Ethiopia. Thus, the long-run lower major crops TFP remained a challenge in rural Ethiopia (Asefa, 2011; Berisso and Heshmati, 2020).

In Ethiopia, inefficiency due to insufficiency of technology and inputs is a common phenomenon in the same agro-ecology reaching different productivity records (IFDC, 2012). Insufficient inputs for all and, unfavorable policies and strategies are also hindering issues for the productivity of crops in SSA (Kassie, 2010; Abafita et al., 2016). There is a vast mismatch between the amount of cultivable land and inputs consumed for the last two decades in Ethiopia (Rashid *et al.*, 2013; IFDC, 2015; Bachewe *et al.*, 2015).

Though labor-intensive technologies are a vehicle in this sector, their adoption and efficiency remained insignificant in Ethiopia (Bezu *et al.*, 2014). Heavy dependence on rainfall makes the area vulnerable to seasonal rainfall shocks (Spielman *et al.*, 2010). Among the others, maize, teff, barley, wheat, sorghum, and Enset are the most growing crops in various agro-ecologies of the research area. However, the region was characterized by low TFP and inefficiency due to smallholding, high climate variability, and greater resistance to new technology adoption (Gebeyehu, 2016).

Moreover, the economic theories suggest per capita expenditure is the best indicator of welfare but presupposes that households maximize a continuous utility function defined over commodities. However, in developing countries there is an inverse relationship between productivity and poverty in rural people. Rural poverty due to low productivity growth has been a long-standing challenge with uneven progress across Africa (WFP, 2016; Adeyemi, 2017).

Low crop productivity in Southern Nations, Nationalities, People's Region (SNNPR) was due to weak adoption of inputs and technologies, poor irrigation schemes, and misuse of family labor (Hagos et al., 2016). Despite there has been substantial production growth in crops due to the expansion of area cultivated and technology use since growth transformation plan one (GTP-I), the yields haven't fulfilled the food and nutrition requirement of people in the region. The uncertain rainfall distribution, weak work attitude, insufficient inputs for all, and inefficient agronomic practices become challenges in the SNNPR (NPC, 2016; Abagissa, 2018).

Against the above backdrop, this research contributes to agricultural economics analysis by substantiating the existing literature and methodologies and providing policy recommendations that are useful not only for academicians but also for practitioners. Moreover, it contributes to recently developed models of separating inefficiency into persistent, transient, and farm-heterogeneity based on empirical evidence. It provides valuable information for policymakers to establish due policies and strategies that can improve efficiency and responsiveness to TELCs in the study area.

It also identifies policy issues that can shift the status of inefficiency components. Finally, according the researcher's understanding, it could be the first research, addressing the problems of household and farm heterogeneities by using strongly balanced short panel data in Southern Ethiopia's major crops farming.

1.3.Objectives of this Dissertation

1.3.1. General Objective: the general objective of this study was to analyze the input intensity use effect on TFP, and its impact on rural poverty in Southern Ethiopia.

1.3.2. Specific Objectives were: **-**

- Analyzing the impact of agricultural input intensity of use on TFP of major crops in Southern Ethiopia;
- Examining the share of TE and TC as growth component of major crops TFP in the area;
- Identifying factors affecting persistent and transient inefficiency of major crops produced in the study area;
- Analyzing the impact of TFP on rural poverty in Southern Ethiopia.

1.4.Philosophical Orientation of the Study

Theory-based research stimulates knowledge for the understanding and applicability framework of research (Brierley, 2014). Thus, any scientific research requires a theory or thought and knowledge of the related research philosophies that can underpin different principles of the inquiry. In any study, the philosophy that underpins the study is outlined in various research paradigms (Ahrens, 2008; Tashakkori and Teddlie, 2010; Adom et al., 2016).

Thus, the pragmatism paradigm is preferred and presented below. Since there is the possibility to depict paradigms on a continuum with positivism/post-positivism at one end and, constructivism at the other end, pragmatism in the middle of both, can be the best-fit philosophy for social research. This approach authenticates the researchers in the upshots of truth, fact, and helps intuitive appeal on the issues (Creswell, 2009; Lincoln et al., 2011, Brierley, 2014). It also perceives issues differently in different scenarios and permit different views and interpretations of the world (Ihuah et al., 2013).

Therefore, a pragmatic approach provides a balanced point between the deductive and inductive perspectives of thinking which offers practical answers for merging different paradigms. As a result, Creswell (2009) suggested that a pragmatic research approach seemed to be the most prominent paradigm with a strong philosophical relationship for a mixed-method approach. Moreover, the pragmatic approach provides a better grounding to fully explore the complex phenomenon instead of using a single method approach in the research. Thus, quantitative research is objective and qualitative research is subjective, a pragmatic approach to research challenges the traditional distinction between both of these in the conduct of research (Morgan, 2007; Creswell et al., 2017; Adom et al., 2016).

The pragmatic approach allows researchers to be flexible enough to adopt the most practical approach to address research questions. By doing so, there are singular and multiple realities derived from both quantitative and qualitative research. Therefore, pragmatic research philosophy is a skeleton for mixed methods of research. This approach has also a strong philosophical foothold in the mixed methods or methodological pluralism camps (Kalolo, 2015; David, 2015; Kivunja, 2017). Hence, this study used these methods within pragmatic philosophy.

1.5.Research Methodology, Design and Approach

As Creswell et al., (2017) suggested, the mixed methods approach provides opportunities to compensate the inherent methods weaknesses, strengths and offset inevitable method biases. Thus, it enables a greater degree of understanding to be formulated than adopting a single approach to specific studies. In the social study, analyzing the qualitative and quantitative data in triangulation is executed simultaneously and rigorously by integrating the two forms of data. Triangulation provides opportunities for convergence and corroboration of the research results. Therefore, this design has the potential for further research that could be required as a result of discrepancies within the data sets (Flowers, 2009).

The primary purpose of using triangulation mixed methods design is to determine theory-based triangulation on how events occur and influence particular production of the sector. The other rationale is that it assists to justify the reasons behind the phenomenon of the relationship between technology and TFP growth in a given sector (Kivunja, 2017). Furthermore, triangulation has many advantages on such kind studies in strengthening the validity of the result to robust valid results (Sellitz et al., 2015). Therefore, due to scientific and conceptual reasons discussed above, mixed methods and triangulation in harmony made this research a tool for other research.

Table 1.1. Summary of Methodological Approaches

Chapter/ Objective	Model		References	Justification/Reasons
	Name	Equation/Formula		
Chapter two	DRF model under exogenous and endogenous treatment regression approaches	ATE (x, t) = E ($y_1 - y_0$|x, t) and ATE = $E_{(x,t)}${ATE(x, t)}	Cerulli, 2015	The reasons:- -The treatment variable is continuous. -HHs' reaction is heterogeneous to observable confounders -The selection into treatment is endogenous. Limitation of the model:- -Ignores estimation of generalized propensity score -A Heckman bivariate selection model, which requires additional distributional assumptions.
	Fixed effect model	$y_{it} = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} \ldots + \delta_t + \varepsilon_{it}$	Evenson et al., 2009 Wossen et al., 2019	-Overcome the unobserved specific fixed-effects; -Remove omitted variable bias across time; -Avoids the possibility of simultaneity biases resulting from the endogeniety of some regressors
	Estimating production functions using the control function approach Levinshon-Petrin (LP).	$lny_{it} = \alpha_0 + \beta_{it} + \beta_{it} + \cdots + \text{epsilon\_it}$	Wooldridge, 2016; Van Beveren, 2012 Levinsohn et al., 2003	Requires intermediate inputs to proxy for unobserved productivity and uses only strongly balanced panel data.
Chapter three	A TVIDM with deterministic, and stochastic components models	$\Delta TE = -\frac{\partial u}{\partial t}$ and $\Delta TC = \frac{\partial \ln f\ (X_{it};\theta)}{\partial t}$	Kumbhakar *et al.*, 2015 Colombi et al., 2014 Lai and Kumbhakar,2018	Reasons:- - It can fix inefficiency for a given individual - It can change over time and across individuals. - It can be measured through production function. - It can be measured by ΔTE, ΔTC.

Chapter Four	***FE-model***	$y_{it} = \sigma_0 + f(X_{it};\theta) + \varepsilon_{it} - u_i$	Schmidt and Sickles (1984). Agasisti et al., 2017	assumes inefficiency effects to be time-invariant and individual specific as well as abled to offer estimates of persistent/long-run inefficiencies
	TFE-model	$y_{it} = \sigma_0 + f(X_{it};\theta) + \mu_i + V_{it} - \alpha_{it}$ $\alpha_{it} \sim N^+(0, \beta_\alpha^2)$, $V_{it} \sim N^+(0, \beta_v^2)$, and $\mu_i \sim N^+(0, \beta_\mu^2)$	Greene (2005a) Berisso and Heshmati, 2020	-separate transient/short-run inefficiencies from persistent individual effects. -separately treat time-invariant farm heterogeneity and transient inefficiency effects
	KH-model	$y_{it} = \sigma_0 + f(X_{it};\theta) + \pi_{it}$ Or $y_{it} = \sigma_0 + f(X_{it};\theta) + \varepsilon_{it} - \omega_i - \varphi_{it}$	Kumbhakar and Heshmati, 1995 Heshmati *et al.*, 2016 Berisso and Heshmati, 2020	Estimates of persistent and transient inefficiencies without accounting for farm heterogeneity. It split the error term into three components where ε_{it} captures a random shock; ω_i captures individual effects as persistent inefficiency; and φ_{it} captures the transient inefficiency component.
	KLH-model	$y_{it} = \sigma_0 + f(X_{it};\theta) + \mu_i + V_{it} - \omega_i - \varphi_{it}$	Kumbhakar et al., (2015) Colombi et al., 2017	It provides estimates of persistent and transient inefficiencies separating them from time-invariant farm effects and noise. It decomposes error term into four components.
Chapter Five	A TVIDM with deterministic, and stochastic components models	Same with Chapter three	Same with Chapter three	Same with Chapter three
	FEM by using RCEPC	$lnC_{it} = \alpha_i + \beta Prod_{it} + \gamma X_{it} + \varepsilon_{it}$	Foster,J.E. (2009)	To find poverty by using real consumption expenditure
	FGT indices	$P_{\alpha,t} = \frac{1}{\sum_i^n w_{it}} \sum_{i=1}^{n} \left(\frac{Z - \widehat{C_{it}}}{Z}\right)^{\theta} w_{it} I_{it}$	McGuire, 2015; Ajayi et al., 2020	To find performing a poverty prediction by using static FGT indices of poverty

1.5.1. Data set

The qualitative data collection undertook from Wolita, Sidama, and Gamo zones and the regionals Bureau officials for triangulation. On the other hand, secondary data from the ESS collected and created strongly balanced panel data. The data management process was aggregating major crops like sorghum, teff, barley, maize, and wheat in value-generating other explanatory variables: land size in a hectare, labor force, the values of farm capitals, and livestock ownership in TLUs, RCPC and other dummy variables prepared for analysis (Mekonnen and Bamlaku, 2017).

The dissertation made use of a mix of several methods as appropriate to each objective addressed in each chapter. The estimation of TFP was using the control function approach like LP (Van Beveren, 2012).

1.6.Conceptual Framework

The extent of using new major crops input adoption/diffusion; TE and TC have either positive or negative impact on productivity in general and TFP in particular. Understanding the farm level adoption and aggregate level adoption also helps to differentiate the level of inefficiency and its impact on rural poverty. Diffusion of a certain technology on a given geographical area justifies how and why farm households choose technologies among the available sets of technologies (Spielman et al., 2010; Gray et al., 2011; Marenya, 2012, Pretty, 2014).

The adoption and diffusion of various agricultural inputs of major crops: varieties, insurance, or innovative lending can increase productivity and reduces poverty in rural areas. Moreover, due to risk and uncertainty during production, illiteracy, inaccessibility of input, credit constraints, and tenure insecurity can cause low adoption of inputs. Resource use efficiency, farm capital, and TELC (factor-product and product-product production relationships) can determine crop productivity (Debertin, 2012; Sime, 2015; Guan *et al.,* 2015).

Efficiency enhancement skills and management practices and, technological improvements are influential factors of TFP. Agricultural production can be inefficient due to failing to achieve maximum output from a given level of inputs (technical inefficiency). The poorest households are more prone to shocks, the illness of a cultivator, and drought which minimizes TFP growth (Alemu 2015, Agasisti, et al. 2017; Berisso and Heshmati, 2020).

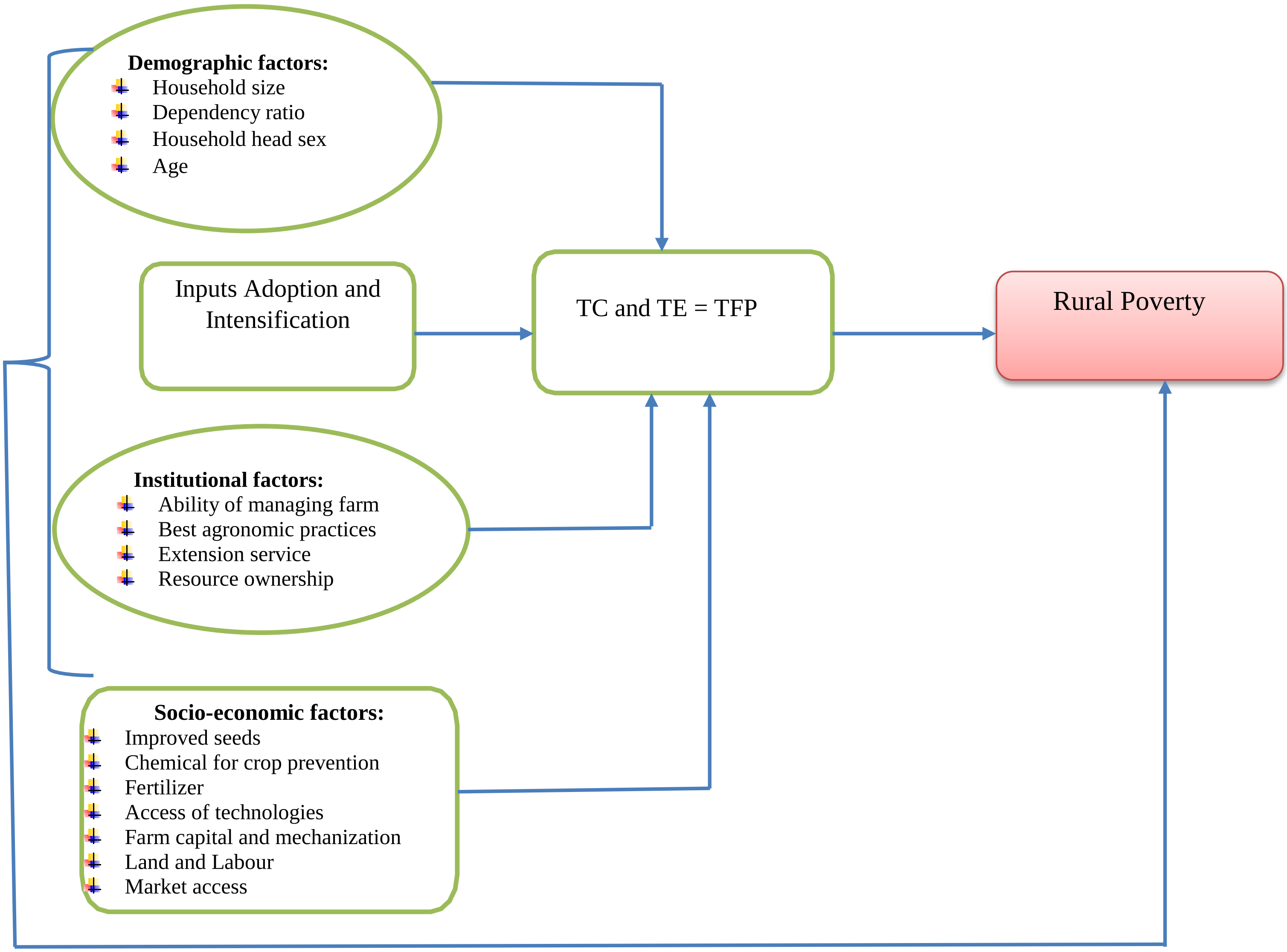

Figure 1.1. Conceptual Framework

Source: Own Illustration

1.7.Organization of the Dissertation

This thesis is organized in five separate chapters. The first chapter is the introductory chapter narrates thesis that gives an overall introduction of the issue, statement of the problem, objectives of the dissertation, and methodological approaches including the datasets used in the study. Chapters 2-5 present four inter-related yet independent chapters. The second chapter[1] examines the impact of agricultural inputs on the TFP. Chapters three and four have already been published in the Sustainability journal by MDPI in Switzerland Basel, and The JDA Department of Economics and Finance, Tennessee State University, USA, respectively. The third chapter focuses on the TE and TC as function of TFP.

This chapter has provided a detailed inferential analysis on TE and TC as the components of TFP. The fourth chapter identified the heterogeneity, transient and persistent production efficiencies of crops in southern Ethiopia. This chapter filled the cramped gaps of information and knowledge of sources of persistent, transient, and farm-heterogeneity inefficiency in the study area. The fifth chapter[2] analyzes the impact of TFP growth on rural poverty in Southern Ethiopia. Finally, chapter six concludes the research and draws several important policy implications from the empirical findings of the study.

[1] Its revised version is submitted to the journal and, currently, we are waiting for the reviewers' reply.
[2] Its revised version is submitted to the journal and, currently, we are waiting for the reviewers' reply.

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CHAPTER TWO

IMPACT OF AGRICULTURAL INPUTS INTENSITY USE ON THE PRODUCTIVITY OF MAJOR CROPS IN SOUTHERN ETHIOPIA[1]

Abstract

Evidence shows that the rate of input use is decisive for productivity growth; the percentage of farmers who applied fertilizer has slow progress in Ethiopia. Studies suggested possible ways of addressing in the limitations of understanding the empirical knowledge and methods. This study analyzed the impact of agricultural input use to augment the productivity of major crops. A panel data of (2011, 2013, and 2015) acquired from the Ethiopian socio-economic survey was used. It was analyzed using the basic fixed effect model and dose-response function under exogenous and endogenous treatment models. In the exogenous and endogenous treatment cases, households applying fertilizer have achieved actual yields with different levels of higher outputs than their counterparts. In endogenous treatment, the household applying fertilizer harvested higher output than those in the counterfactual condition. Though factors affecting the products of crops have a significant effect on their productivity, the level of its impact varies in both exogenous and endogenous treatment approaches. On average, its productivity was 6.16 per year and exhibited a clear upward trend for the first two rounds. Although the upward trend declined from 2013-2015, the overall productivity increased in the survey years. Moreover, inputs: fertilizer, seed, labor force, farm capital use have a positive effect on aggregate outputs of considered crops. Findings pinpoint the policy that farmers should focus on intensity use of inputs and improve production.

Keywords: Treatment effects, Dose-response function, Productivity, Fertilizer, Intensity.

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1. INTRODUCTION

Globally, agriculture experienced a shift in a farming system that expresses the transition from zero-input agriculture to intensive input and other post-harvest technologies; from hand, hoe to plow culture; from animal-drawn to tractor-drawn cultivation; and from traditional farming to mechanization. Therefore, a practice of intensive agricultural input use is considered a vital stimulus for raising productivity. However, the level of intensity of inputs and the shift in the farming system differs in LDCs. Comparatively; farmers in most LDCs are confronted with the intricacies of accepting and using mechanized inputs to increase productivity (Minot et al., 2005; Bachewe et al., 2015). Though it is suggested that improved varieties of inputs, post-harvest technologies, and best agronomic practice can determine agricultural growth, there are challenges in applying the inputs and technologies in most LDCs (Wang et al., 2002; Boserup, 2007; Sime et al., 2015; Guan et al., 2015).

However, adoption is the integration of technologies into farmers' normal agricultural production process. The main drivers of adoption are risk management, learning, information, credit availability, taste preferences, agro-ecology, local costs, and benefits. An individual can take action to discontinue the use of new inputs for personal, institutional, and/or social reasons. Based on that fact, adoption is classified in to two: individual farm level and geographical area level. In the first case, adoption depends on the use of technology in the long-run equilibrium whereas, the aggregate adoption depends on adopting the new inputs at the level of the geographical area (Seo and Robel, 2008; Rashid et al., 2013; Headey et al., 2014; Adhikari et al., 2015).

On the other hand, diffusion implies agricultural input adoption is measured within a given geographical area, except for those indivisible inputs (Evenson et al., 2009; Liu, 2013). Theoretically, farmers have to choose a combination of inputs or technologies that maximize their expected production. A package of technologies could provide higher productivity than pieces of technologies used individually. However, pervasive uncertainty about new technology and binding credit constraint can confound this notion of complementarity. The adoption decision-making also involves how much resource or inputs to be used (Holden, 2014; Ma and Shi, 2015).

There are no exact paths to guide farm intensifications in developing countries. However, depending on resource endowments, a particular group of households can choose the Labor-led intensification path, committing a higher level of labor inputs per unit of land. While others can embark on capital-led intensification involving increased investments in non-labor inputs (Spielman et al., 2012; Holden, 2014).

More specifically, the fertilizer use effect is higher than other inputs that can lag crop productivity growth. Africa soils experienced inherent difficulties in the shortage of nutrient, leaching the soil, and continuous soil erosion. The variability in the adoption rate of inputs is one of the main reasons for slow progress in agricultural productivity in SSA countries (Gebeyehu, 2016; Christiaensen, 2017; Wossen et al., 2019). Moreover, in agriculture, innovation often takes the form of the use of modern inputs and farming practices: seeds, fertilizer, crop protection chemicals, and integrated soil and water management practices to address a wide range of production limiting constraints (Kassie et al., 2010; Headey et al., 2014; Alia, 2017).

Ethiopian agriculture is composed of 12.6 million smallholders and several hundred large-scale farms. Thus, 71% of total output produced from cereals, pulses, and oil crops are obtained annually. The remainder of 29% is the aggregate of others in Ethiopia (Mondal et al., 2018). On the other hand, the econometric models examine the causal link between TFP with its key inputs share. That is due to the scanty impacts of input intensity based on a panel data framework at the regional level. Estimate the causal effect of the treatment variable on an outcome through both exogenous and endogenous treatment effects by controlling function models (Cerulli, 2015).

Against all mentioned backdrop, this research analyzed the impact of agricultural input use in TFP of aggregate major crops in SNNPR Ethiopia. Though Ethiopian socio-economic survey (LSMS-ISA) is a nationally representative and freely available dataset for all crop types, this research focused on SNNPR and specific crops for the following reasons: firstly, SNNPR is one of the regions with more than 30 million populations that are highly vulnerable for drought more than the rest regions. Next, it is one of the three potential regions producing those considered crops exceptionally, on fragmented landholding.

Then, as the Central Statistics Authority (CSA) definition, those crops are categorized as the major crops for their coverage and market value throughout the country. The reason for selecting those five major portions of cereals (teff, wheat, maize, sorghum, and barley) was due to the crops are the core of Southern Ethiopia's dominantly for food requirement, and constitutes more than 84% of calories consumed (Hagos et al., 2018). Thus, understanding the means of enhancing production levels and reducing their variability is an essential concern for researchers to improve (Tafessse et al., 2012).

Furthermore, it is difficult to measure the amount of fertilizer consumed by each crop; aggregation of fertilizer consumed in considered crops at the household level was the only option at hand for the researchers in the area. The intermediate inputs are fertilizers, pesticides, and seeds. Among others, teff, barley, wheat, maize, and sorghum crops, receive 95% of inputs purchased and imported by the country (Hagos et al., 2016).

Furthermore, this research is relevant to enhance the TFP of those crops, the rural development of the region by filling up the cramped gap in information and knowledge about the effects of input use on TFP. Besides, this research contributes to the existing literature by identifying the level of agriculture input intensification in TFP. Eventually, the organization of the article is as follows: first, reviewing empirical and theoretical literature on the concept of agricultural input adoption and intensification followed by dose-response models under exogenous and endogenous treatment. Then, the article presented the data sources and data set, as well as the model adopted. Third, the result of the analysis presented, with detail discussion. Finally, the article concludes by providing plausible recommendations in the last section.

2. METHODOLOGY

2.1.Dataset

The regional heads, three Zonal, and district office heads were selected as KII, purposively. The enumeration areas (EAs) with two focus group discussions (FGDs) holding ten households were chosen purposively. The qualitative data was collected through semi-structured interviews, FGDs, and key informant interview (KII). The reason was to supplement the quantitative data to analyze the topic. Inclusive questionnaires of household demographic and agricultural information from Ethiopian socio-economic survey (ESS) data sets were used.

In the data management, 2,187 households balanced panel data created for SNNPR as the secondary data. However, some of the missing indicators of productivity of considered crops: soil fertility, the slope of plots, and land tenure status, especially in (2011 and 2013) datasets. Aggregation of those major crops valued in three steps. First, the conversion of local units of measurement was done in a standard measure (Kg).

Conversion factors, prepared by the CSA at the *Kebele* (*Kebele* is the most diminutive administrative structure next to the district) level unit prices was collected. Finally, the value of production is generated by multiplying the average unit price at *the Kebele* level held. Next, monetary values by using the unit price of production were collected. Then, the monetary value of production was created by multiplying the mean unit price at *the village* level and the quantities produced. Based on the conversion factors (CF) of CSA, landholdings of the households were converted into standard measure (hectare) (Bachewe, 2009).

As aforementioned, variation in labor use time throughout the panel years brings measurement errors. The labor force calculation was as follows: first, the ages of each household member were sorted using the standards in the adult equivalent. Next, the conversion of days to a week and then to the annual level was carried out. Then, based on their category (men, women, and children), the labor forces are obtained through multiplication. The sum of the number of water storage pit; water pump; sickles; hoes; *Mofer* (*Mofer* is one of the farm capital which could be tied with Kenber and pulled by the oxen); *Kenber (Kenber* is also the farm capital used to plow land putting on the heads of oxen with Mofer*);* traditional plow, and modern plow converted. The qualities of the assets owned are expected to increase the risk of measurement errors in the data. Measurement of Livestock ownership in TLUs following as Jahnke (1982) was done.

2.2.Sampling techniques and sampling size Determination

The probability proportion technique was executed to select 74 EAs from ten to two households from the sample of 30 Agricultural Sample Survey (AgSS). In all three years (2011, 2013, and 2015), the chosen EAs and the households for quantitative data collection were remained the same.

2.3.Model specification

Fixed-effect and dose response function (DRF) models were employed for the analysis of the study. Resource economists have used production or response functions to perform economic analyses of resource production decisions of efficient use of fertilizer. DRF model through a regression approach was employed in the study for the following reasons: for the treatment is continuous, the households react heterogeneously to observable confounders it helps to know whether the selection into treatment is endogenous or not. Further, the two estimation procedures contemplated by the DRF model are based on OLS under conditional mean independence and IV when selection endogeniety is assumed (Cerulli, 2015).

Moreover, the fixed-effect model is employed for the benefit to: overcome the unobserved specific fixed-effects, remove omitted variable bias across time, and avoids the possibility of simultaneity biases resulting from the endogeniety of some regressors (Evenson et al., 2009; Wossen et al., 2019).

To identify households' aggregate major crops production by using basic fixed-effects specification is as follows:

$$y_{it} = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} \ldots + \delta_t + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} = \mu_i + V_{it} \quad (2)$$

Where Y_{it} average aggregate considered crops of household i in year t; x is the averages inputs used. Meanwhile, a period dummy δ_t is used to flexibly capture global trends is a household fixed-effect, and *it* is a random error term.

The other one is DRF under EET models used with the regression approach. Three reasons why EETMs were selected for this study as are follows: first, the treatment variable is continuous. Second, households' reaction is heterogeneous to observable confounders. Finally, the selection of treatment is endogenous. Therefore, the DRF is equal to the Average Treatment Effect (ATE) given the level of treatment (t) or ATE (t), with t representing the continuous treatment variable. However, the models have limitations in ignoring the generalized propensity score and a Heckman bivariate selection model estimation which requires additional distributional assumptions (Cerulli, 2015).

Therefore, we considered two different and exclusive potential outcomes: one referring to the unit i when treated (Y_1) and the second referring to the same unit when untreated (Y_0). Define fertilizer $_i$ (F_0) as the treatment indicator, taking value 1 for treated and 0 for untreated units, and define $X_i = (X_{1i}, X_{1i}, X_{1i}, X_{1i}, X_{1i}, X_{Ki})$ as a row vector of K exogenous and observable characteristics (confounders) for unit i = 1, . . . , N. Let N be the total number of units, N_1 be the number of treated units, and N_0 be the number of untreated units, with $N = N_1 + N_0$. Given the above model notation, we assume a specific population generating process for the two exclusive potential outcomes:

$$\text{Fertilizer=1: output} = 1: y_1 = \mu_1 + g_1(x) + h(t) + \varepsilon_1 \quad (3)$$

$$\text{Fertilizer=0: } output = 0: \; y_0 = \mu_0 + g_0(x) + \varepsilon_0 \quad (4)$$

Where $g_1(x_i)$ and $g_0(x_i)$ as the unit i's responses to the vector of confounding variables ***x*i** when the unit is treated and untreated, respectively. Assume μ_1 and μ_0 to be two scalars, and assume ε_1 and ε_0 to be two random variables having 0 unconditional mean and constant variance. t_i taking values within the continuous range (0, 100) as the continuous treatment indicator, and $h(t_i)$ as a general derivable function of t_i where the h**(t)** function is different from 0 only in the treated status (Wooldridge, 2016).

Given this, we can also define the causal parameters of interest. Indeed, by limiting the treatment effect (TE) as TE=($y_1 \;\; y_0$), we set the causal parameters of interest as the population ATEs conditional on x and t; that is,

$$\text{ATE}(x, t) = E(y_1 - y_0 | x, t) \quad (5)$$

$$\text{ATET}(x, t > 0) = E(y_1 - y_0 | x, t > 0) \quad (6)$$

$$\text{ATENT}(x, t = 0) = E(y_1 - y_0 | x, t = 0) \quad (7)$$

As ATE indicates below the overall average treatment effect, ATET (the average TE on treated), and ATENT (the average TE on untreated units). By the law of iterated expectation, the population unconditional ATE was obtained as:

$$\text{ATE} = E_{(x,t)}\{\text{ATE}(x, t) \quad (8)$$

$$\text{ATET} = E_{(x,t>0)}\{\text{ATE}(x, t > 0)\} \quad (9)$$

$$\text{ATENT} = E_{(x,t=0)}\{\text{ATE}(x, t = 0)\} \quad (10)$$

$$\text{ATE}(t) = \{\text{ATEN} + (h(t) - \bar{h}_{(t>0)} \quad \text{if } t > 0 \text{ and when ATENT become } t = 0 \quad (11)$$

1. Estimation under Unconfoundedness

Unconfoundedness states that conditional on the knowledge of the true exogenous confounders X, the conditions for randomization are restored and causal parameters become identifiable.

$$E(Y_{ji}/ F_i, t_i, X_i) = E(Y_{ji}|X_i) \text{ with } j = \{0, 1\} \quad (12)$$

The conditional mean independence assumption is a sufficient condition for identifying ATEs and the DRF in this context.

$$E(Y_{ji}/F_i, t_i, X_i) = \mu_0 + F_i \times \text{ATE} + X_i\boldsymbol{\theta}_0 + F_i \times (X_i - mean)\ \boldsymbol{\theta} + F_i \times [h(t_i) - \bar{h}] \quad (13)$$

That is possible because these parameters are functions of consistent estimates. Standard errors for ATET and ATENT are obtained via bootstrapping (Wooldridge, 2016). To complete the identification of ATEs and the DRF, we finally assume a polynomial parametric form of degree

$$h(t): h(t_i) = \lambda_1 t_i + \lambda_2 t^2_i + \lambda_3 t^3_i + \cdots + \boldsymbol{\lambda}_k t^k_i \quad (14)$$

2. Estimation under treatment Endogeneity

To restore consistency semi-structural form of instrumental variables was implemented.

$$Y_i = \mu_0 + X_i\boldsymbol{\theta}_0 + F_i \times \text{ATE} + F_i (X_i - mean)\ \boldsymbol{\theta} + F_i T_1 i + bF_i T_2 i + cF_i T_3 i + \alpha_i \quad (15)$$

$$F_i = X_{F,i}\ \boldsymbol{\phi}_F + \epsilon_{F,i} \quad (16)$$

$$t'_i = X_{t,i}\ \boldsymbol{\phi}_t + \epsilon_{ti} \quad (17)$$

Where, $T_{1i} = t_i - E(t_i)$, $T_{2i} = t^2_i - E(t^2_i)$, and $T_{3i} = t^3_i - E(t^3_i)$; F_i represents the latent unobservable counterpart variable of F_i; t_i is fully observed only when $F_i = 1$ (and $t_i = t'_i$) and otherwise, it was supposed to be unobserved (which is equal to 0); $X_{F,\ i}$ and $X_{1,\ i}$ are two sets of exogenous repressors; $\epsilon_{output,\ i}$ $\epsilon_{t,\ i}$ and α_i are error terms that are supposed to be freely correlated with one another with 0 unconditional means. On Equation (14) the selection equation defines the regression explaining the net benefit indicator of individual output. The vector of covariates $X_{F,\ i}$ are the selection criteria used, for instance, by an agency to set the treated and untreated groups.

In turn, on equation (17), the treatment level equation defines how the level of unit treatment is decided and only considers units that were eligible for treatment. Finally, the vector of covariates $X_{t,\ i}$ are those exogenous variables that were considered determinants of the treatment level. In equation (13), $X_{F,\ i}$, T_{1i}, T_{2i}, and T_{3i} are endogenous, with the latter three being functions of the endogenous t. In general, with two endogenous variables, the identification of equation (14–17) required the availability of more than two instrumental variables exogenetic.

Based on the above equations, it is possible to estimate a Heckman two-step procedure. The Heckman two-step procedure performs a probit of individual output on ***X*****,** F_i in the first step, using only the N_1 selected observations. These all were to obtain unbiased and consistent estimators. In the second step, the OLS regression of t ′ i on x t, i, augmented by the Mills' ratio obtained from the probit in the first step, using all the N observations as predictions for the censored data (Cerulli, 2015; Wooldridge, 2016). Therefore, variables like ages of the households head and households who participated in extension program were considered as the endogenous variables and the control variables were gender of the household heads, households participated in erosion prevention, access for irrigation, oxen and value of farm capital.

The estimation of TFP was using the control function approach. It includes Levinshon-Petrin (LP) estimation methodologies. By default, the output was transformed by logarithm through time. The reasons for using LP estimation algorithm is, it requires intermediate inputs to proxy for unobserved productivity and uses only strongly balanced panel data.

Thus, Cobb–Douglas productions function in logs:

$$logy_{it} = \beta_0 + \ \beta_1 logx_{1t} + \beta_2 logx_{2t} + \ \beta_3 logx_{3t} \ldots + \varepsilon_{it}$$

Where, $\mathrm{logoutput_{it}}$ is the logarithm of output, $\mathrm{land_{it}}$, $\mathrm{seed_{it}}$, $\mathrm{labor_{it}}$, $\mathrm{fertilzer_{it}}$ and $\mathrm{oxen_{it}}$ is the logarithmic inputs that all of which are observed. Then, TFP was obtained through prediction in the prodest-production function estimation method (Levinsohn et al., 2003; Van Beveren, 2012; Wooldridge, 2016).

Table 2. 1.Variables Expected Signs

Variable Description	Expected Sign
Amount of seeds used	Positive
Fertilizer used	Positive
Landholding in hectares	Positive
Labor force which is equivalent to man-days	Positive
The number of plowing oxen	Positive
Participation in Extension system	Positive

Note: Aggregate Output of major crops is the dependent variable.

Source: Illustrated from the above-Reviewed works of literature.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics of Dose-response function

This study analyzed the impact of fertilizer use on the TFP of crops grown in Southern Ethiopia: Teff (Eragrostis tef) (Teff is the staple and small size local cereal originated from Ethiopia), wheat (Triticum aestivum), maize (Zea mays), barley (Hordeum Vulgare), and sorghum (Sorghum bicolor). Though the logarithmic values of inputs and aggregated crop output were used in estimating the DRF models, the logarithmic values of some variables resulted zero which could become undefined. Thus, the variables with zero values were changed to nearly zero (0.0001) value before transformation. It was consistent with the findings of Wassie (2014). Various tests were executed before the analysis.

The probability distribution allowed being normal. The treatment variable was fertilizer application on those aggregated crops. Histograms and summary statistics indicated that the treatment variable is distributed normally. Likelihood ratio test (LR test) is performed to compare the goodness of fit of the two models of which a null model against an alternative one to see the fitness of the two models. Then, the null hypothesis (H_0) is rejected due to the larger model with the addition of two dummy variables (irrigation access and major crops damage opportunity), which has significant improvement over the smaller one within the selected model. Endogeneity test of Durbin–Wu–Hausmantest Durbin Wu (DWH) is implemented (Baum et al., 2007).

The endogeniety test indicated that the H_0 is rejected with the value of $p<0.001$, and the explanatory variables have endogeniety. Based on the t-test, H_0 is rejected due to the mean of both treated and untreated households was significant with the value of $p<0.001$.

The conventional inputs are chosen together with the treatment variable. Therefore, the transformed inputs: land size owned by the households, farm capital, oxen plowing, and labor force (equivalent to the man-days). The aggregate value of considered crop outputs is considered as a dependent variable at the household level. Moreover, fertilizer is a continuous treatment variable (dose) in the study.

A 38.04% variation in the outputs of considered major crops within the household is captured by the model (i.e., it indicates how good the explanatory variables account for changes in outputs within each household over time). 63.66% of the variance is due to differences across panels. The corr (u_i, X_b) = -0.6618, means the correlation between u_i and fitted values of explanatory variables is -0.6618. As land covered by the considered crops varies across time by 10%, its outputs increases by 2.8%. Moreover, a 10% increase in the number of oxen to plowing, seed, and labor force appears to increase outputs of considered major crops by 0.44%, 0.3%, and 0.22%, respectively. In other words, it is possible to argue that intensive use of inputs is imperative in increasing the production of those crops. Like other inputs discussed above a 10% increment in fertilizer, consumption is estimated to improve 0.14% of considered crops, indicated that there is input complementarity in the study area (Table 2.2).

Table 2.2.Estimates of Fixed Effect Model (n=1,954)

Variables	Coefficients	Robust Std.Err.	t-test	P>|t|
Constant	-88.151**	41.966	-2.10	0.036
Logarithm of area cultivated	0.28***	0.058	4.79	0.000
Logarithm of number of plowing oxen	0.044 ***	0 .008	5.40	0.000
Logarithm of seed used in Kg	0.030***	0 .007	4.46	0.000
Logarithmic value of fertilizer used	0.014**	0.007	1.86	0.006
Logarithm of labor force in man-days	0.022***	0 .008	2.90	0.004
Male headed households	-0.479*	0 .20	-2.37	0.018
Households participated in extension program	0. 99***	0 .102	9.71	0.000
Households credit access used	0.432***	0 .092	4.67	0.000
Logarithmic value of households distance in (KMs) to nearest the market	-2.080***	0.480	-4.33	0.000
Year	0.051*	0.021	2.46	0.014
Sigma_u	1.418			
Sigma_e	1.072			
Rho	0.637			
corr(u_i, Xb) = -0.6618				
R-sq:				
within = 0.3804				

Legend: ***Significant at * p<0.05; ** p<0.01; *** p<0.001

Source: Authors' Computation.

Consistent with the authors of (Alemu and Bishaw, 2015) stated that households who used fertilizer packages have a surplus of 109% increment of considered crop output than their counterparts. Households who applied oxen to plow, seed, and labor force, fertilize in the production process achieved a much higher surplus than their complements. Moreover, the production of households who didn't apply fertilizer in the considered crops is estimated to decline the outputs by 153.6% (Table 2.3).

Table2. 3. Difference between Fertilizer Users and Non-users by Observable Covariates

Variables	Mean Diff	Std.Err.	[95% Conf. Interval]	
Logarithm of aggregate output of major crops produced (untreated)	-1.09***	0.07	-1.23	-0.96
Logarithm of land cultivated in hectare (untreated)	-0.65***	0.05	-0.75	-0.56
Logarithm of labor force (untreated)	-1.07***	0.24	-1.54	-0.59
Logarithm of fertilizer consumption (untreated)	-15.36***	0.04	-15.44	-15.28
Logarithm of seed used (untreated)	-3.62***	0.26	-4.13	-3.09
Logarithm of number of plowing oxen (untreated)	-4.81***	0.24	-5.27	-4.34
Households who participated in the extension program (untreated)	-0.57***	0.02	-0.60	-0.53
Male headed households (untreated)	-0.09***	0.02	-0.13 -	-0.06
Households who used credit service (untreated)	-0.47***	0.02	-0.51	-0.44
Households who used chemicals for the prevention of crops from damage (untreated)	-0.24***	0.02	-0.28	-0.20
Households' with irrigated land (untreated)	-0.15***	0.02	-0.19	-0.11

Legend: ***Significant at $p<0.01$

Source: Authors' Computation.

Households who participated in the extension program and applied fertilizer for the considered crops indicated a significant difference with their counterpart. The male-headed houses that utilized fertilizer become benefited by a 9% surplus of production than the non-users. Similarly, those households who produce considered crops with the chemicals for crop-protection and without the use of fertilizer have lost 24% of the outputs than the counterpart during the years. Thereby, a 15% loss of output for households who have access to irrigation water without the use of fertilizer was estimated during the survey years (Table 2.3).

3.2. Estimation of Dose-response function under exogenous treatment

The total value of output and fertilizer was scrutinized as the outcome, and treatment variables, respectively. The controls from the explanatory variables: age, the gender of the household heads, participation in the erosion prevention and extension program, access for irrigation, numbers of farm capital owned, landholdings, oxen for plowing, and labor force used in the production of crops in SNNPR. The treatment effect (fertilizer application) on aggregate output indicated that fertilized land is estimated to a 15% higher yield than its counterparts (Table 2.4).

Consistent with the findings of (Mekonnen, 2017; Seifu et al., 2019), the ages of household heads who applied fertilizer were affirmed to have a positive effect and increments by one more year, which implies the slight increments in the productivity of major crops by 0.01 units. A 10% increment in the involvement of the extension system of households who applied fertilizer brought a 5.7% increment in the productivity of considered crops. A 10% increment in the size of irrigated land of households who applied fertilizer is also estimated to improve the productivity of considered crops by 1.04%. A 10% increment in the farming capitals of fertilizer-applying households could increase 0.5% of the mentioned crop output, indicating the crop's productivity depends on the utility level of fertilizer (Table 2.4). On the other hand, the qualitative data indicated that the needs of fertilizer consumption were fluctuated due to the agricultural market failures. It contradicts the findings (Goshu et al., 2019). However, it is consistent with the study of (Taffesse et al., 2012).

Table2. 4. Estimation of Dose-Response Function as Exogenous Treatment Case

Logoutput	Coeff.	Std. Err.	t-test	[95% Conf. Interval]	
Treatment	0.15***	0.09	2.81	0.07	0.41
Household head's gender	0.13***	0.07	2.42	0.03	0.30
Household's that have irrigation access	1.04***	0.06	16.94	0.93	1.18
Extension program participated	0.57***	0.17	3.30	0.23	0.91
Logarithmic Value of farm capita in number	0.05***	0.01	5.05	0.04	0.09
Logarithmic Value of oxen	0.03***	0.01	5.47	0.02	0.04
_ws_age of heads of the household	0.01***	0.003	3.52	0.004	0.01
_ws_extension	-0.98***	0.19	5.24	-1.34	-0.60
_ws_erosion prevention	0.28***	0.08	3.69	0.13	0.43
Tw_1	0.1***	0.03	3.05	0.04	0.17
Tw_2	-0.01***	0.001	-3.52	-0.008	-0.002
Tw_3	0 .00004***	0.00001	3.49	0.00002	0.00006
__cons	6.1***	0.35	17.52	5.42	6.78

Legend: ***Significant at $p<0.01$; Coeff. = Coefficients

Source: Authors' estimation.

The DRF indicates the relationship is weakly increasing and quite precisely estimated for both higher and lower the value of fertilizer in the study area. Therefore, DRF is more strongly decreasing some values of outputs estimation becomes increasing for higher levels of dose or fertilizer to improve the productivity of considered crops. In other words, the minimum dose of fertilizer application was around 70 where the DRF correctly exhibits a flex point, indicating that production of higher output demands at least 70% application of fertilizer. Thus, as the dose of using fertilizer increases, the proportion of output produced could increase (Figure 2.1).

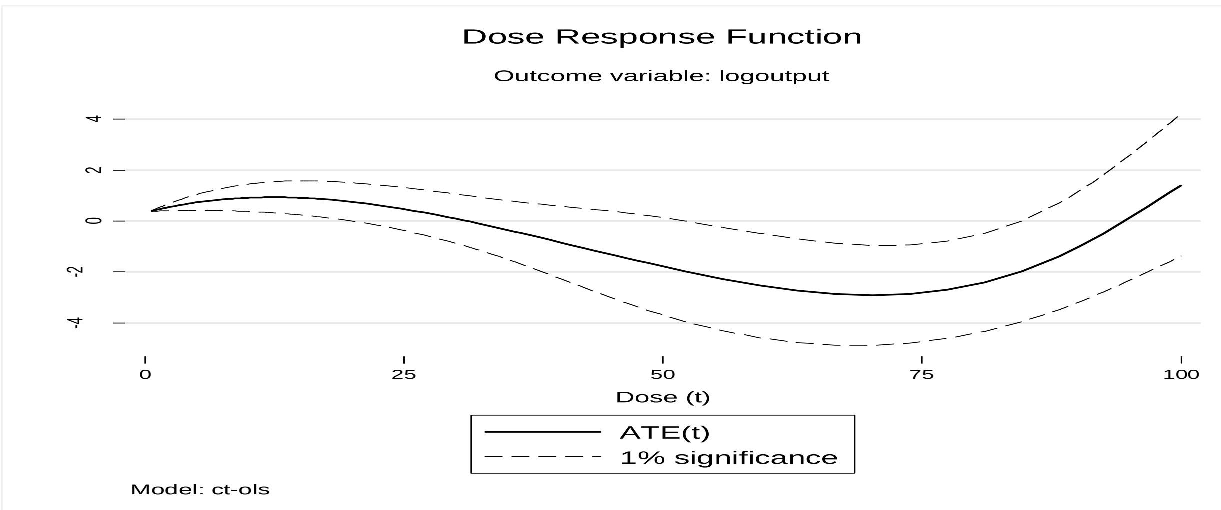


Figure 2.1 Dose-Response Function of Fertilizer on Aggregate Outputs of Major Crops; Exogenous Treatment Case

However, the derivative of DRF with its confidence interval improved the dose level that can enhance productivity. As the parabola of derivative DRF is a cubic function of the previous DRF, the minimum dose becomes between 40-50 where the DRF correctly exhibits a flex point. The derivative dose-response showed that the decreasing and later increasing tendencies were initially downward sloping and later upward sloping trends of fertilizer application, indicating both negative and positive impacts on the productivity of considered major crops (Figure 2.2).

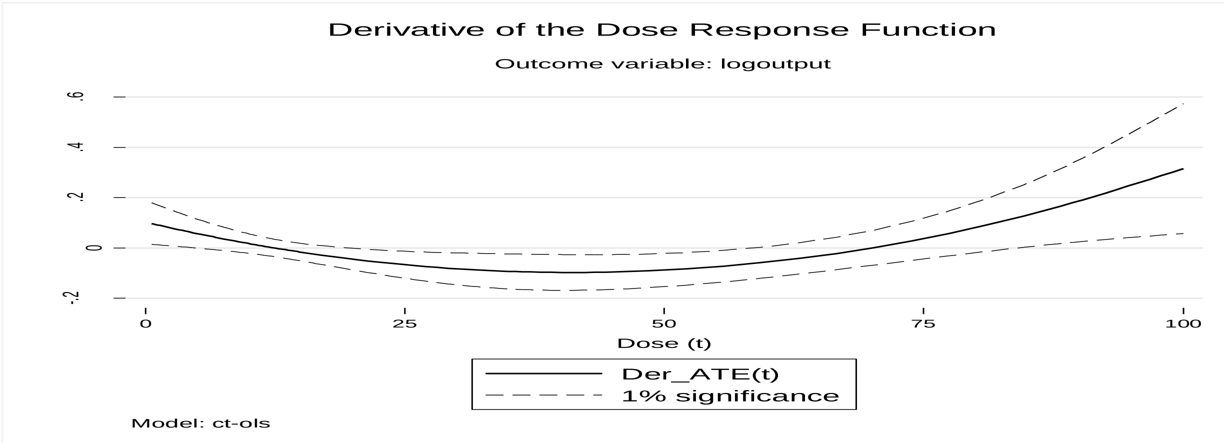


Figure 2.2.Derivative of the Dose-Response of Function of Fertilizer on Aggregate Outputs of Major Crops; Exogenous Treatment Case

Estimated DRF in Figure 1 and its derivatives in Figure 2 indicated that the households who applied fertilizer in their considered major crops at higher doses increase their productivity. Analogously, the minimum requirement of fertilizer to increase the productivity of considered crops was 70 in DRF of Figure 1. However, 40-50 in derivatives DRF of Figure 2 shows fertilizer applying households using at least 40-50 of a dose can produce higher outputs.

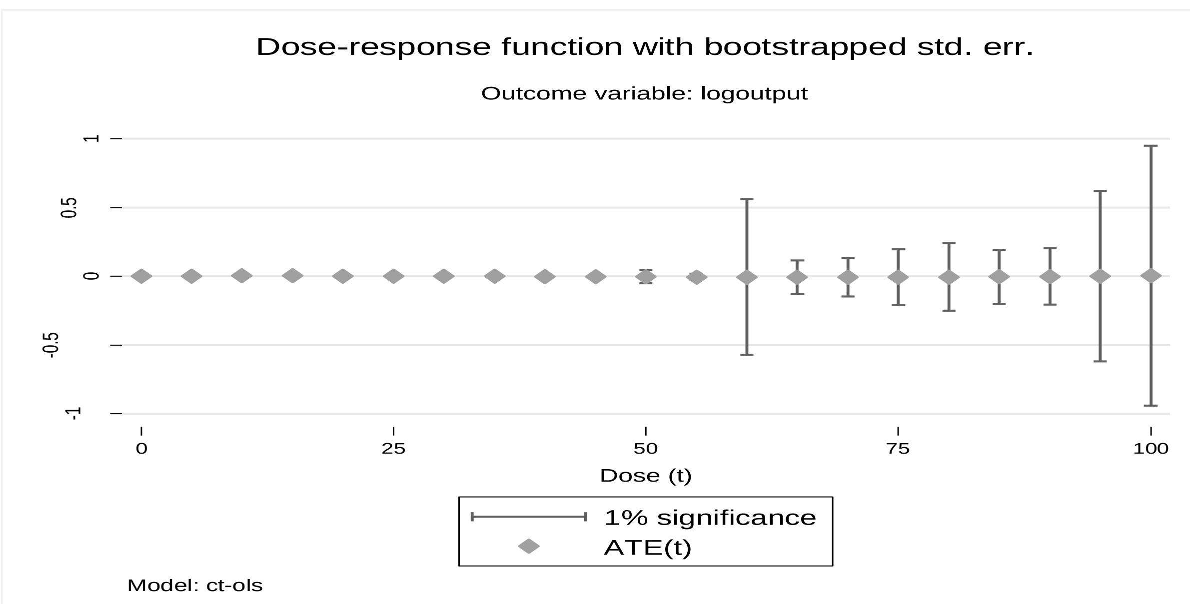


Figure 2.3. Dose-Response of Function of Fertilizer on Aggregate Outputs of Major Crops; Exogenous Treatment Case with Bootstrapped Standard Errors.

3.3. Estimation of Dose-response function under endogenous treatment

In estimating the DRF under endogenous treatment, 782 censored and 1,173 uncensored observations appeared for the analysis. The 61% variability in productivity appeared due to differences across the survey years. The fertilizer application is considered as dependent variable and gender of the household heads, extension program, irrigation access, value of oxen, farm capital, land size and credit access are used as determinants of fertilizer application. Thus, observed value of fertilizer for the value of seed in the analysis; the coefficients on gender of the household heads, extension program, irrigation access, value of oxen, farm capital, land size and credit access level represent the estimated marginal effects of the regressors in the underlying regression. The explanatory variables had a positive effect on the aggregate output of major crops (Table 2.5).

The coefficient of second-stage variables (3.55) was much larger than that of the first-stage estimate (2.57). The variances of the variables in the first stage (1.27) are higher than the variance of the variables in the second stage (0.19) indicated that the higher variance of the variables is the best reason for the coefficient's lower value (Table 2.5).

Consistent with the previous studies of (Wendland et al., 2008; Kassie et al., 2010; Van Der Westhuizen et al., 2017), a 10% increment of irrigated land by the households who applied fertilizer, brings nearly a 2.5% increase in the aggregate output of major crops. Households with farm capitals who apply fertilizer can get 6% higher production of considered crops than their counterparts (Table 2.5).

Table 2.5.Two-step Estimation of Heckman Selection Model

Variables	Coeff.	Std. Err.	z-test	[95% Conf. Interval]	
fertlizer2					
Male headed households	-0.28*	0.38	0.74	-0.46	1.02
Access for irrigation (yes=1)	-0.45*	0.34	-1.32	-1.12	0.22
Participation in extension system	-2.19**	1.20	-1.81	-4.56	0.18
Logarithmic value of oxen	0.02*	0.05	0.43	-0.07	0.12
Logarithmic value of farm capital	0.11	0.13	0.86	-0.14	0.36
Logarithmic value of land size in ha	0.56*	0.16	3.48	0.25	0.88
Credit access (yes=1)	0.61*	0.32	1.94	-0.01	1.23
_cons	2.57**	1.28	2.01	0.07	5.07
Treatment					
Male headed households	0.04*	0.09	0.44	0.03	0.20
Access for irrigation (yes=1)	0.25***	0.09	2.94	0.41	0.80
Participation in extension program	1.73***	0.09	19.94	1.90	2.56
Logarithmic value of oxen	0.05***	0.01	8.21	0.04	0.06
Logarithmic value farm capital	0.06***	0.02	3.53	0.03	0.09
Logarithmic value of seed	0.003***	0.01	4.69	0.002	0.04
_cons	3.55***	0.19	18.44	3.18	3.93
Mills					
Lambda	3.06	1.46	2.10	0.20	5.92
Rho	0.61				
Sigma	5.06				

***Significant in <1%; **Significant in <5%; *Significant in <10%; Coeff. = Coefficient

Source: Authors' estimation.

Consistent with findings (Prety, 1997; Bellemare, 2013; Mekonnen, 2017), the logarithmic values of landholding, seed, and households who used credit services are considered instrumental variables for 2sls estimation. The ages of household head and households participated in the extension program were taken as the endogenious variables in the analysis. The estimation result of the impact of applying fertilizer by using instrumental variable revealed that households who applied fertilizer are estimated to harvest 111% higher output than their counterparts. The age of household heads is also statistically significant at the 10 percent level, implying that as the age of the household head increases by one more year, the outputs of aggregated major crops exhibit a slight increment by 0.009 units. About, 10% increment of irrigated land for the fertilizers applying households could increase 10.4 % of outputs (Table 2.6).

Table 2.6. Instrumental Variables by Two-Stage Least Square (2SLS) Regression

Logoutput	**Coeff.**	**Std. Err.**	**t**	**[95% Conf. Interval]**	
Treatment	1.11*	0 .66	1.69	-0.18	2.39
_ws_age	0.01*	0 .004	2.10	.0006	0.02
_ws_extension	-4.21***	1.17	-3.61	-6.50	-1.93
Tw_1	0.371*	0.16	2.28	0.05	0.69
Tw_2	0.003*	0 .02	017	-0.03	0. .04
Tw_3	-0.0001*	0 .0002	-0.29	-0.0005	0.0003
Male headed households	-0.12*	0 .18	-0.68	-0.48	0.24
Access for irrigation (yes=1)	1.04***	0 .13	8.11	0.79	1.29
Households participated in extension (yes=1)	2.21*	0.97	2.28	0.31	4.11
Logarithmic value of oxen	-0.02*	0.01	1.56	-0.005	0.05
Logarithmic value of farm capital	0.03*	0 .02	1.44	-0.010	0.07
_cons	0.58*	2.10	0.28	-3.54	4.71

Instrumented: treatment _ws_age _ws_extension Tw_1 Tw_2 Tw_3

Instruments: sex dmmirrig extension logoxen logfarm_capita probw _ps_age _ps_extension T_hatp_1 T_hatp_2 T_hatp_3

Note: Coeff.= Coefficient ***Significant in <1%; **Significant in <5%; *Significant in <10%; Coeff. = Coefficient Source: Authors' estimation.

In the endogenous treatment, DRF indicated that the relationship variables slightly increasing for the values of dose. DRF has slightly increased some value of treatment estimation for higher fertilizer application in the mentioned crops. Therefore, the maximum dose of fertilizer application was around (90-100) dose, where the DRF correctly exhibits a flex point, indicating that improvement in the expected productivity (Figure 2.4).

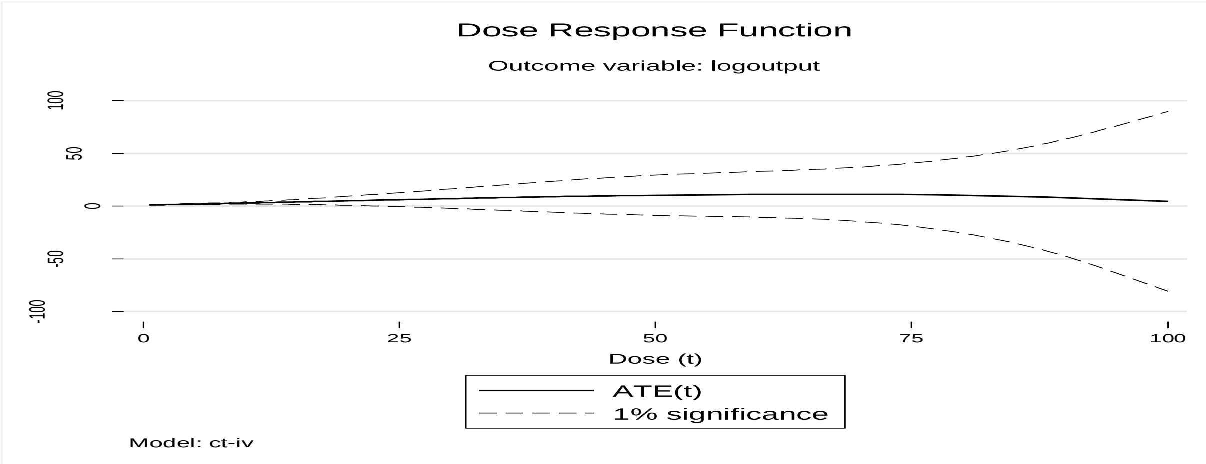


Figure 2.4. Dose-Response Function of Fertilizer on Aggregate Outputs of Major Crops; Endogenous Treatment Case

In endogenous treatment, the dose-responses and derivative demonstrations have similar tendencies for the outputs of considered crops. However, the minimum dose trends of fertilizer in the dose-response and derivative were varying so far. This result was dissimilar to the one obtained using the exogenous treatment. As indicated earlier by Morea et al., (2012), on average, 54.8% of households can consume fertilizer in 2011/12 to enhance their production of considered crops. The average number of households who have been utilizing fertilizer increased from 63.4% to 64.9% (2013-2016) (Figure 2.5).

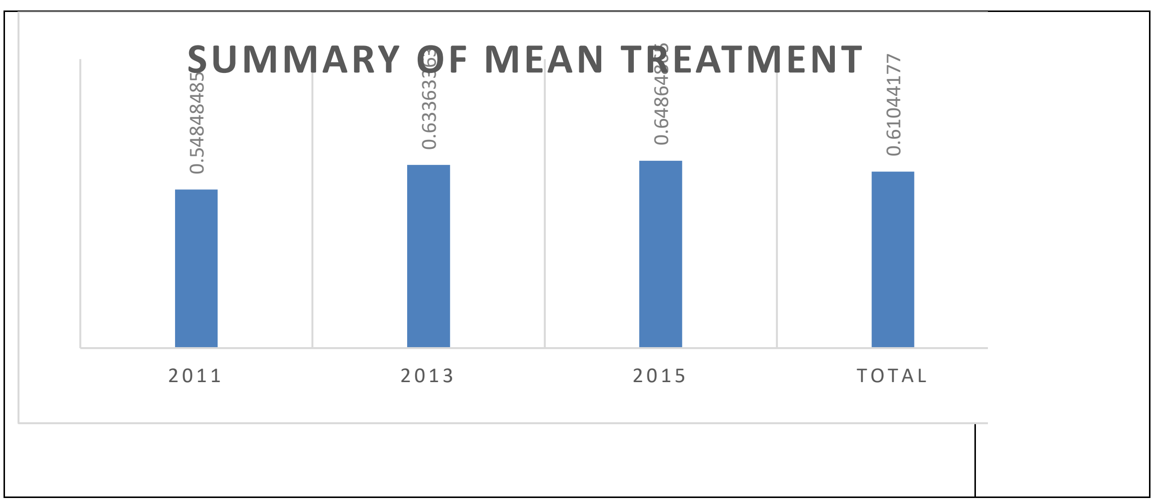
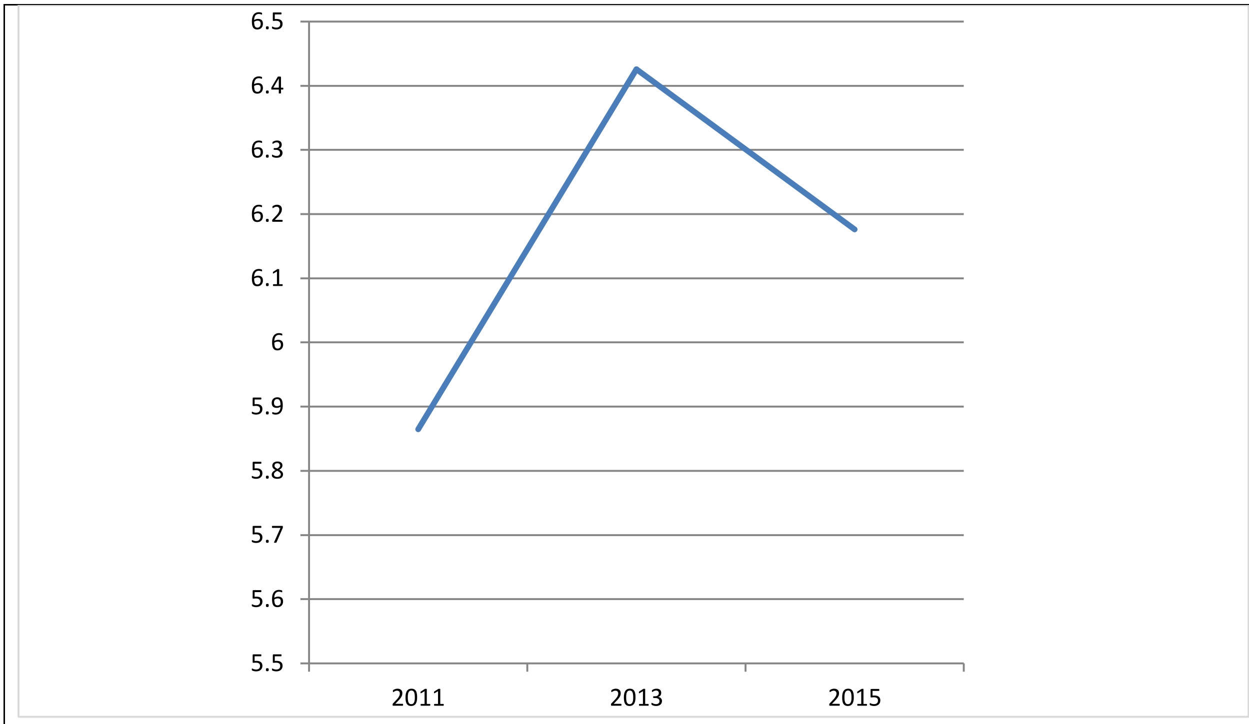


Figure 2.5. Summary of Treatment.

3.4. Treatment effect on total factor productivity of major crops

Following theoretical acknowledgment of Holden, (2014); Alia, (2017), in this study, the average TFP obtained was 6.16 during the survey years indicates; productivity of considered major crops exhibited a clear upward trend between 2011/12 to 2013/14 and bent down from 2013-2015 in the area. Though aggregated outputs of crops increased from 2011/12-2013/14, there was a slow reduction in TFP in 2015/16. In both exogenous and endogenous treatments, the outputs of crops treated households were statistically significant (Figure 2.6). Consistent with the study (Goshu et al., 2019), KII indicated that fertilizer consumption is troublesome due to its packaging in large volumes for all land in the study area.



Average TFP

Figure 2.6. Summary of total factor productivity during the survey years.

4. CONCLUSIONS AND POLICY IMPLICATIONS

In the case of endogenous treatment, the households have got much larger outputs than in exogenous treatment. When the extension service participant increases by one unit in the exogenous and endogenous treatment cases, the farm household outputs of considered crops enhanced significantly by 0.57unit and 1.73 units, respectively. Intensification is the ideal source of productivity growth. Thus, land size, fertilizer use, extension service, and farm capital are the main determinants of the productivity of considered crops.

The fertilizer application is considered as dependent variable and gender of the household heads, extension program, irrigation access, value of oxen, farm capital, land size and credit access are used as determinants of fertilizer application. Thus, observed value of fertilizer for the value of seed in the analysis; the coefficients on gender of the household heads, extension program, irrigation access, value of oxen, farm capital, land size and credit access level represent the estimated marginal effects of the regressors in the underlying regression.

Moreover, inputs: land covered by those crops, number of oxen; seed, and labor force in man-days can positively affect the level of production across time. Households with irrigated land irrigated and applied fertilizer have a significant proportional effect on the level of considered crop production. Generally, households who treat fertilizer for the output growth have achieved 109% surplus of production. Agricultural input intensified in the production of those crops has a pivotal role in enhancing productivity.

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CHAPTER THREE

TOTAL FACTOR PRODUCTIVITY OF MAJOR CROPS IN SOUTHERN ETHIOPIA: A DISAGGREGATED ANALYSIS OF THE GROWTH COMPONENTS[1]

Abstract*:*

Despite the importance of agriculture to the Ethiopian economy, there was slow progress total factor Productivity. Researchers suggested possible ways of addressing the productivity of the crop sub-sector. Nevertheless, there are gaps in the empirical literature in both knowledge and methods. The aim of this research is examining the productivity of teff, maize, barley, wheat, and sorghum. The Living Standard Measurement Survey data is executed to estimate Cobb-Douglass stochastic production function. Thus, a time-varying decay model with deterministic and stochastic components was adopted. The impact of input on the production of considered crops was significant at the 1%. Variation in the inefficiency term explained 46.4% of the total variance in the composed error term. The mean response for technology was 22% in the study area. The findings pointed out the policy-makers have to take attention in intensifying those intermediate inputs.

Keywords: Cobb-Douglas production function; efficiency; technical-change; productivity; major crops.

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1. INTRODUCTION

Achieving overall growth in agricultural production and reducing poverty are the major priorities of LDCs. Hence, in LDCs, advancing farm inputs, technology and producer efficiency are very critical issues for development (Gray et al., 2011). However, sources of productivity growth are significantly different from region to region. For instance, in Asia, crop productivity growth is driven by intensification, whereas in South America, its growth is due to improvement in labor productivity, efficient adoption of new farm technology, and efficiency. In Africa, growth goes against intensification than more from area expansion (Brink et al., 2009; Sandhu, 2019).

Though agriculture is the dominant economic sector in Ethiopia, the GDP share of the sector is below 50% and remains highly vulnerable to extravagancy of nature (Hagos et al., 2016). Therefore, increasing the share of sectors to its economy and improving the status of intensification are fundamental. Evidence shows that there was 37% inefficiency (inefficiency can occur if a particular product is not possible to produce a given production with at least one input is called technically inefficient) in the product of cereal-crops in Ethiopia (Wassie, 2014). However, sources of inefficiencies differ from area to area (Shumet, 2011; World Bank, 2016).

The land covered by teff (24%), maize(16.98%), sorghum (14.97%), and wheat (13.49%) of the total grain cultivation, 87% was produced by these crops in Ethiopia (McGuire, 2015; Abafita et al., 2016; Sandhu, 2019). Comparatively, the productivity of those crops in SNNPR was estimated below the national average, except for maize crop in the last two decades. In the 20th Era, those intermediary inputs are considered as the determinant factors that can affect productivity of crops. Crop TFP is defined as how efficiently inputs of agricultural production are utilized. As TFP is a concept that describes changes in the efficiency of which inputs have transformed into outputs. In addition to this, TFP can also be determined by analyzing how efficiently inputs have been used in the production of agriculture. However, TE and TC are components of TFP remained an area of research in LDCs (IFAD, 2016; Balié and Ghins, 2017).

On the other hand, previous studies based on cross-sectional data and SF approach measured at the various local levels (Gollin, 2010; Ndulo, 2011; Kathuria, 2013). Therefore, research with panel-data and SF approach fulfills the knowledge gap in the field. While TFP measurement is most appropriate to analyze dynamics of TFP; the vast majority of statistical analysis has been conducted using partial factor productivity in Ethiopia (Kitila et al, 2014; Ajadi et al., 2017).

Furthermore, poor infrastructure, limited credit service for smallholders, fewer export crops, inadequate agricultural market are also the main constraints that hinder crop productivity (Davidson et al., 2013; Alemu, 2015). Insufficient inputs for all and, unfavorable policies and strategies are also hindering issues for the productivity of crops in SSA (Kassie, 2010; Abafita et al., 2016). There is a vast mismatch between the amount of cultivable land and inputs consumed for the last two decades in Ethiopia (Rashid et al., 2013; IFDC, 2015; Bachewe et al., 2015).

Among the others, maize, teff, barley, wheat, sorghum, and Enset are the most growing crops in various agro-ecologies of the research area. However, the region was characterized by low TFP and inefficiency due to smallholding, high climate variability, and greater resistance to new technology adoption (Gebeyehu, 2016). Low crop productivity in SNNPR was due to weak adoption of inputs and technologies, poor irrigation schemes, and misuse of family labor (Hagos et al., 2016).

Against the above backdrop, this research analyzes TE and TC as part of TFP in SNNPR. This research contributes on the existing theory of production. Moreover, it shares relevant information about how to improve the productivity of those crops in the area. The reminder of the article is presented as follows: the first part deals with data sources and the models adopted for analysis. The second part presents the analysis followed by a nuanced discussion of pertinent issues. Finally, the article concludes by putting the statement of actionable recommendations.

2. Methodology

2.1. Dataset

The regional heads, three Zonal, and district office heads were selected as key informant interview (KII), purposively. The EAs with two focus group discussions (FGDs) holding ten households were chosen purposively. The qualitative data was collected through semi-structured interviews, FGDs, and KII. The reason was to supplement the quantitative data to analyze the topic. Inclusive questionnaires of household demographic and agricultural information from ESS data sets were used.

In the data management, 2,187 households balanced panel data created for SNNPR as the secondary data. However, some of the missing indicators of productivity of considered crops: soil fertility, the slope of plots, and land tenure status, especially in (2011 and 2013) datasets. Aggregation of those major crops valued in three steps. First, the conversion of local units of measurement was done in a standard measure (Kg).

Conversion factors, prepared by the CSA at the *Kebele* (*Kebele* is the most diminutive administrative structure next to the district) level unit prices was collected. Finally, the value of production is generated by multiplying the average unit price at *the Kebele* level held. Next, monetary values by using the unit price of production were collected. Then, the monetary value of production created by multiplying the mean unit price at *the village* level and the quantities produced. Based on the CF OF CSA, landholdings of the households were converted into standard measure (hectare) (Bachewe, 2009).

As aforementioned, variation in labor use time throughout the panel years brings measurement errors. The labor force calculation was as follows: first, by sorting the age of each household member using the standards in the adult equivalent. Next, the conversion of days to a week and then to the annual level was carried out. Then, based on their category (men, women, and children), the labor forces are obtained through multiplication. The sum of the number of water storage pit; water pump; sickles; hoes; *Mofer* (*Mofer* is one of the farm capital which could be tied with Kenber and pulled by the oxen); *Kenber (Kenber* is also the farm capital used to plow land putting on the heads of oxen with Mofer*);* traditional plow, and modern plow converted. The qualities of the assets owned are expected to increase the risk of measurement errors in the data. Measurement of TLUs following converted Jahnke (1982).

2.2.Sampling techniques and sample size Determination

The probability proportion technique was executed to select 74 EAs from ten to two households from the sample of 30 AgSS. In all three years (2011, 2013, and 2015), the chosen EAs and the households for quantitative data collection were remained the same.

2.3. Model Specification

The TVID model with deterministic and stochastic-components were used to estimate households' efficiency on the basis of assumption that unobserved individual-error as random and a deterministic function of time-dummies (Kuosmanen, 2009; Colombi et al., 2014). These models were selected over the other panel data models of the production function as it drops the entire incidental parameters problem in the analysis (Kumnhakar et al., 2014). Thus, this model fixed inefficiency for a given individual and changed it over time and across individuals. The parametric deterministic production frontier is presented as follows:

$$y_{it} = f(X_{it};\theta) * \exp(-\mathrm{u}) \qquad (1)$$

where y_{it} is the scalar output of a producer, $f(X_{it};\theta)$ is the deterministic part of SPF with technology parameter vector θ to be estimated, $X = (X_1, \ldots X_n) \geq 0$ is an input vector, **t** is a time trend serving as a proxy for TC, and $u \geq 0$ represents output-oriented technical inefficiency. From this production frontier, the rate of TC is measured as follows:

$$\Delta TC = \frac{\partial \ln f\,(X_{it};\theta)}{\partial t} \qquad (2)$$

Then, ΔTC would have three chances: being a value greater than, less than or equal to zero as TC shifts the production frontier up, leaves it unchanged, or shifts it down, respectively. Similarly, the rate of change of TE ΔTE is also measured as:

$$\Delta TE = -\frac{\partial u}{\partial t} \qquad (3)$$

Where ΔTE is TE, the inefficiency term ∂u, is always between 0 and 1, where ∂u is equal to zero, then production is on the frontier and ΔTE = 1, therefore a farmer is technically efficient. When ∂u is greater than zero, the farmer is technically inefficient ($\Delta TE < 1$), since production is below the frontier (Ayle et al., 2006; Abro et al., 2014).

$$\begin{aligned} lnoutput_{it} &= \beta_0 + \beta_1\, lnland_{it} + \beta_2\, lnoxen_{it} \\ &\quad + \beta_3\, lnseed_{it} + \ldots + \beta_n\, lnlabor_{it} + \beta_n\, lnfertilizer_{it} + \varepsilon_{it} \end{aligned} \qquad (4)$$

i = 1…., I and t = 1…, T $and\ \varepsilon_{it} = V_{it} - U_{it}$ (5)

where $\varepsilon_{it}$is the composed error terms $V_{it}\ and\ U_{it}$. V_{it}, is a non-negative random variable (inefficiency) term, assuming its distribution as half-normal distribution above zero of the $N(\mu, \sigma_u^2)$ distribution. Error terms $U_{it}\ and\ V_{it}$ are the idiosyncratic and inefficiency components of the composed error term in the same order, ε_{it} of producer i at time period t (Abro et al., 2014; David, 2015).

$$u_{it} = \gamma u_i = \{\exp[-\gamma(t-T)]\}u_{it} \text{ and } TE_{it} = \mathrm{E}\left[exp(-{}^{u_{it}}/_{\varepsilon_{it}})\right] \quad (6)$$

Where, γ is the unknown scalar parameter and T is the last period for which observations for the i^{th} households were obtained. This model assumes that u_{it} decreases, remains constant or increases, as $\gamma > 0$, $\gamma = 0$ or $\gamma < 0$, respectively. Setting $\gamma = 0$ provides the time invariant model. On the other hand, $\gamma > 0$ implies households tend to improve their efficiency over time and vice versa. V_{it} is assumed to be independently and identically distributed. Thus, based on these assumptions, the probability density function of the composite error term ε_{it} and its log-likelihood function are derived for the model using maximum likelihood estimation technique. The predicted value of TE for producer *i* in period *t* is the conditional expectation of the inefficiency component in the error term.

The TFP was estimated using the control function approach like LP approach (Levinsohn et al., 2003; Van Beveren, 2012; Wooldridge, 2016). The logarithmic transformation was performed in the output variable through time.

Thus, Cobb–Douglas productions function in logs:

$$logy_{it} = \beta_0 + \beta_1 logx_{1t} + \beta_2 logx_{2t} + \beta_3 logx_{3t} \ldots + \varepsilon_{it} \quad (7)$$

Where, $\mathrm{logoutput_{it}}$ is the logarithm of output, $\mathrm{land_{it}}$, $\mathrm{seed_{it}}$, $\mathrm{labor_{it}}$, $\mathrm{fertilzer_{it}}$ and $\mathrm{oxen_{it}}$ is the logarithmic inputs that all of which are observed. Then, TFP was obtained through prediction in the prodest-production function estimation method (Levinsohn et al., 2003; Van Beveren, 2012; Wooldridge, 2016).

Table 3.1.Descriptions of Variables and Expected Signs

Variable Description	Expected Sign
Amount of seeds used	Positive
Amount of fertilizer consumed in (kg)	Positive
Landholding in hectares	Positive
Labor force	Positive
The number of ploughing oxen ownership	Positive
Participation in extension system	Positive
Households head age	Negative
Male head of the household	Positive

Note: Aggregate Output of considered crops is the dependent variable.

3. RESULT AND DISCUSSION

3.1. Growth Rate of Input Use and Output of Aggregate Crops

The major crops are as follows: Teff (*Eragrostis tef* is an annual grass with small-sized seed originated from Ethiopia used to prepare Ethiopian flat bread called 'Enjera'), wheat (*Triticum aestivum*), maize (*Zea mays*), barley (*Hordeum vulgare*), and sorghum (*Sorghum bicolor*) (Hagos et al., 2016). The volume of output is improved for all crops, except for sorghum showed a negative growth rate in the study area.

More specifically, 2011/12 as the base year, the AGR of maize production showed a slight increment from 9.79% in 2013/14 to 11.17% in 2015/16 (Table 3.2). This is consistent with the claim by a similar study (Ayele, et al., 2006) and contradictory with the findings of another study (Taffesse et al., 2012) over the last five decades. Therefore, it is possible to argue that households engaged in relatively better agronomic practices are more likely to enhance maize crop production than other crops under consideration in the study area.

Table 3.2.Average Growth rate of Volume of Production of Major Crops in SNNPR

Major Crops	AGR of major crops in %	
	2013/14	2015/16
Barley	53.61	37.41
Maize	9.79	11.17
Sorghum	-26.24	-31.97
Teff	41.28	30.23
Wheat	29.79	25.08

Source: Authors' estimation.

Though there is a significant improvement in participation in the extension program, crop rotation activities, use of irrigation facilities, and access to credit service, there was a slight decline in fertilizer consumption during 2013/14 as compared to that of 2011/12. Though 45% of households participated in the extension program and 57% of households irrigated their land in 2013/14, this data might be exaggerated based on the number of aggregate outputs during 2013/14.

Table 3.3.Mean Values and AGR of Households Input–Output Data Used in SPF (2011-2016)

Variables	2011	2013	2015	AGR in %
Households irrigation use (Yes = 1)	0.13	0.57	0.16	-44.83
Participation in extension program (Yes = 1)	0.27	0.45	0.45	15.38
Credit service used (yes =1)	0.29	0.37	0.36	5.88
Prevention measures of crop by chemical (yes=1)	0.39	0.51	0.53	10.42
Households participated in crop rotation (yes=1)	0.37	0.40	0.43	7.5
Amount of fertilizer used (in Kg)	71.56	61.64	66.8	-0.52
Households seed used (in Kg)	2.90	14.99	19.69	57.14
Labor force (man-days)	319.6	388.6	412.4	10.4
Area cultivated (in hectare)	0.92	1.07	0.95	-3.06
Number of ploughing oxen	0.82	1.15	1.14	9.62
Real value of output produced (in Kg)	1,035	1,092	1,241	10.51

Source: Authors' calculation.

About 15.22% increment of land coverage from 2011/12 to 2013/14 declined by 10.38% in 2015/16. Therefore, it is possible to argue that increment in the bulk of production of crops considered mainly comes from area expansion (Table 3.3). It contradicts the findings' of similar studies (Ajadi et al., 2017). However, it is consistent with the findings of another study (Coelli, 2005).

3.2. Estimation Result of the Cobb-Douglas Production Function

Though the logarithmic values of inputs and aggregated crop output were used in estimating the models, the logarithmic values of some variables resulted zero which could become undefined. Thus, the variables with zero values were changed to nearly zero (0.0001) value before transformation. It was consistent with the findings of Wassie (2014). The validity of models and various tests were also checked before the analysis.

All explanatory variables were jointly significant in explaining the dependent variable (the H_0:$\beta 1 = \beta 2 = \beta 3 \ldots \beta 6 = 0$) is rejected at p<0.001). Wald tests performed for parametric testing of the null hypothesis (H_0) of no inefficiency is rejected at p<0.001) (Table 3.4). Then, inefficiency effects were present in the model. When it takes values between 0 and 1, the H_0 might be rejected. Alternatively, this is to test whether the SF production function is more appropriate than the conventional one. If the H_0 is not rejected, the SF production function would have the same value as the conventional one. The H_0 for the test of no inefficiency is rejected at p<0.001. It was confirmed that there is half-normal distribution. The H_0 for the test of no half-normal distribution is also rejected at p<0.001 (Table 3.4).

Table 3.4.Generalized Likelihood Ratio Tests for the Parameters of SPF and TE Factors

Hypotheses	**LL H_0**	**LL H_1**	**Test Statistics***	**Critical Value**	**Decision**
$H_0: \beta 1 = \beta 2 = \beta 3 \ldots \beta 6 = 0$	-3421.55	-3411.38	20.34	20.51	Reject H_0
$\boldsymbol{\mu}$ is not half normal distribution **(**H_0: $\boldsymbol{\mu}$ = 0**)**	-3421.01	-3403.62	34.78	22.46	Reject H_0
No inefficiency (H_0: $\gamma = 0$)	-3436.92	-3403.62	66.6	13.82	Reject H_0

Note: LL stands for log-likelihood. Source: Authors' estimation.

To calculate the log-likelihood statistics, the SF model and log-likelihood test achieved the maximized iteration (Table 3.4). The likelihood-ratio test statistic $\lambda = -2\{\log [\text{Likelihood } (H_0)] - \log [\text{Likelihood } (H_1)]\}$ has approximately a chi-square distribution ($\chi 2$), distribution with q equal to the number of parameters assumed to be zero in the H_0; it is compared with the critical values of ($\chi 2$) and decided between the two models (Fare et al., 2008). According to (Akaike's information criterion) AIC and (Bayesian information criterion) BIC presented in (1974), a model with the MLE of the parameters which give the minimum of AIC to be accepted.

Parametric estimation of the Cobb-Douglas production function predicted that the coefficients of plowing oxen, land size, the labor force, and fertilizer consumed, and seed used are statistically significant in affecting the bulk of production of major crops. A 10% increase in the labor force and area covered by the considered crops is estimated to improve aggregate output by 0.336% and 0.648% in the same order. A 10% increase in fertilizer use increase productivity by 0.487% compared to their counterparts (Table 3.5).

Thus, improvement in the use of labor force, fertilizer, and land for the crops considered in this study could have additional production and productivity impact in the study area. Similarly, a 10% increase in the number of plowing oxen and the use of seeds are estimated to increase the output by 0.623% and 0.334%, respectively (Table 3.5). It is consistent with the findings of (Taffessse et al., 2012; Alston et al., 2012; World Bank, 2014).

Table 3.5. OLS Estimates of Cobb-Douglas Production Function (n=1,957)

Variables	Coefficients	Std.Err.	z-test	P>|z|
Constant	7.6667***	0.061	125.59	0.000
Logarithm of area cultivated	0.0648***	0.03	2.18	0.000
Logarithm of ploughing oxen)	0.0623***	0.01	9.61	0.000
Logarithm of fertilizer used in Kg	0.0487***	0.01	10.38	0.000
Logarithm of seed used in Kg	0.0334***	0.01	6.17	0.000
Logarithm of labor force in man-days	0.0336***	0.01	5.77	0.000
/lnsig2v	0.49	0.48	-7.89	
/lnsig2u	0.04	0.02	28.05	
sigma_v	0.97	0.15		
sigma_u	-0.14	0.32		
sigma2	2.64	0.38		
Lambda	0.46	0.08		

*** Significant at $p < 0.01$. Source: Authors' own Computation.

3.3. Estimation of Stochastic Frontier Model

The MLE of parametric time-varying inefficiency Cobb-Douglas SF production function is discussed in Table 3.6. Wald test indicates that all the explanatory variables used in the model significantly explained the dependent variable. The value of eta (η) significantly indicated that the level of inefficiency decays toward the base level declined by a factor of 0.04. It is consistent with the findings of Alston et al., (2012).

Consistent with findings of other studies (Seo, 2008; Ball, 2010; Gray et al., 2011), all of the explanatory variables maintained the expected sign and are highly significant. Variation in the inefficiency term explained 46.4% of the total variance in the composed error term. A 10% increment in the land size and fertilizer consumption is estimated to improve output by more than 1.18%, and 0.41% in the same order. Although the sign of the coefficient of seed is positive, its elasticity compared to other explanatory variables is less responsive to the output (Table 3.6). The findings are consistent with prior studies (Ajadi et al, 2017).

Table 3.6.Results from the stochastic Frontier Model

Variables	Coefficients	Std. Err.	z-test
Constant	7.0938***	0.13	53.50
Logarithm of area cultivated (hectare)	0.1176***	0.04	3.27
Logarithm of ploughing oxen	0.0614***	0.01	8.91
Logarithm of fertilizer used in Kg	0.0411***	0.01	8.11
Logarithm of seed used in Kg	0.0335***	0.01	5.40
Logarithm of labor force in man days	0.0374**	0.01	5.72
/mu(μ)	0.49**	0.48	1.01
eta($\boldsymbol{\eta}$)	0.04**	0.02	2.51
/lnsigma2	0.97***	0.15	6.65
/ilgtgamma	-0.14**	0.32	-0.45
Sigma2($\sigma^2_u + \sigma^2_v$)	2.64	0.39	
Gamma(γ)	0.46	0.08	
sigma_u2(σ^2_u)	1.23	0.38	
sigma_v2(σ^2_v)	1.41	0.06	

Log likelihood = −3394.0797; Wald chi2 (5) = 1020.70; Prob ≥ chibar2 = 0.000; *** $p < 0.01$ and ** $p < 0.05$ Source: Authors' estimation from the SFA model.

The elasticity of the marginal effects of inputs used indicated that increment in the outputs. However, the sum value indicated that, it is diminishing marginal returns to scale (0.29) in the production processes. In other words, a 1% simultaneous increase in the input followed by a less than 1% increase in the aggregate outputs. As (Alston et al., 2012) stated, the increment of mean TE was 38.97%, 41.07%, and 43.35% in three consecutive years. However, about 46.86% of the households are under the category of the minimum range of TE. The maximum numbers of the household that have relatively better TE are 4.55%. Moreover, the model predicted that the mean level of TE for crops is 41.22%. *Ceteris paribus* implying that given the level of input and the existing technology, there is room to boost the production of crops in the SNNPR by 58.78% (Table 3.7). It is consistent with findings of (World Bank, 2014).

Table 3.7.Frequency Distribution of TE of major crops in SNNPR

Frequency Group	Observation	Percent	Min	Max
0.030-0.399	917	46.86	0.036	0.399
0.400-0.499	324	16.56	0.400	0.499
0.500-0.599	368	18.80	0.500	0.599
0.600-0.699	259	13.23	0.600	0.699
0.700-0.791	89	4.55	0.700	0.791
Mean TE= 41.22%	1957	100	0.036	0.791

Source: Authors' estimation from the SFA model**.**

Farming households are less sensitive as 22.41% as to the newly invented technologies in the area. Therefore, the absorption of technological practice is declined in SNNPR.

The TFP growth of those crops in real output was over 6.19 for the inputs used in the production process. However, a diminutive decline in TFP in 2015/16 exhibited a clear upward trend in the period 2011–2013 in the area. Though the upward shift of TFP bent down in the latter two years, the overall growth of TFP is positive throughout the survey years (Table 3.8).

Table 3.8.Summary of mean TC and TFP for major crops in SNNPR

Efficiency parameters	**Survey Year**			
	2011	**2013**	**2015**	**Mean**
TC	0.28	0.21	0.18	0.22
TFP	5.9	6.5	6.2	6.2

Source: Authors' estimation.

3.4. Determinants of Technical Efficiency of Major Crops in Southern Ethiopia

Consistent with other studies (Al-Said et al., 2012; World Bank, 2016), involving in the extension, accessing credit and irrigation appeared to increase the efficiency. However, farmers applying organic fertilizer decline their TFP by 2% (Table 3.9). As KII indicated the reason for low TFP in using organic fertilizer was due to farmers' limited use of organic fertilizer and extension service from the Development Agent (DAs). Therefore, promoting the use of the recommended amount of organic fertilizer would increase the production of those considered crops. These are consistent with the findings of similar studies (Teenagers, 2014; Gelgo et al., 2017; Abebe et al., 2019).

Table 3.9.Determinants of Technical Inefficiency of major Crops in Southern Ethiopia

Variable	Mean diff	Std. Err.	[95% Conf. Interval]	
Household participated in the extension system	−0.09 ***	0.01	−0.11	−0.08
Household Participation in credit service	−0.07 ***	0.01	−0.09	−0.05
Household heads with access to irrigation water	−0.10 ***	0.01	−0.12	−0.08
Household with male headed	−0.03 ***	0.01	−0.06	−0.02
Household who apply crop protection chemicals	−0.06 ***	0.01	−0.08	−0.05
Household heads who read and write	−0.05 ***	0.01	−0.07	−0.04
Household who apply organic fertilizer	0.02 **	0.01	0.01	0.04

*** $p < 0.01$ and ** $p < 0.05$ Note: Source: Estimated from the SFA model.

Consistent with studies (Block, 2010; Ahmed and Degu, 2019), KII indicated that the packaging difficulties of fertilizer lagged the level of its consumption and credit access. In some areas of the region row-sowing for teff crop is a very challenging practices. Due to the diversified agro-ecologies and farming experiences, the SNNPR showed marked variability as one moves from area to area. It is also cause for the failure and slow dissemination of various newly invented techniques in the area.

3.5. Total Factor Productivity Disaggregated by Crop Types

Consistent to Berisso and Heshmati (2020), by using inputs in the production process the TFP growth of each crop is estimated separately in the area. More specifically, the fertilizer use varies from crop to crop. However, the mean consumption of wheat was three folds greater than sorghum. The average seed use of maize and wheat crops was nearly similar throughout the survey years (Table 3.10).

Besides, the households have been using more labor force in the production processes of maize and teff than any other crops included in the study. Among the crops, the average cultivated area allocated for maize was 1.78 hectares of land and had highest TFP than other crops in the area.

The land allotted for maize was six-folds greater than sorghum. The low productivity of sorghum was due to the limited use of fertilizer, seed, labor force, and oxen. The average income generated from sorghum farms was also the lowest indicating that its amount produced and the crop's market value is the weakest compared with other crops (Table 3.10).

Table 3.10. The Average Value of Input-Total Factor Productivity of Major Crops.

Variables	Barley	Maize	Sorghum	Teff	Wheat
TFP of crops	6.36	7.34	4.37	7.13	5.76
Household's fertilizer used (in kg)	35.84	57.27	43.98	56.67	137.83
Household's seeds used (in kg)	7.09	20.73	4.17	8.57	20.24
Labour force used by man-days	315.12	557.69	248.39	557.62	188.77
Area cultivated (in hectare)	0.53	1.78	0.3	0.67	1.61
Oxen allocated for ploughing	1.46	1.06	0.28	1.17	1.19
Household's income generated (in ETB)	20190	22063.5	12181.9	26808.5	16681.8

Source: Authors' estimation.

According to the t-test analysis, teff has covered 0.67 hectares of land on average, and has got higher TFP next to maize comparatively. Participating in extension system significantly affects the TFP of wheat and maize than others. Moreover, credit facility has got a positive effect on all crops, except barley. On the other hand, the crop rotation has got relatively better productivity for barley and wheat than other crops. The literacy rate was also significantly affects the TFP for all the major crops, except sorghum (Table 3.11).

Table 3.11.Determinants of Total Factor Productivity by Crop types in Southern Ethiopia

Variables	Barley	Maize	Sorghum	Teff	Wheat
Participation in extension program (Yes = 1)	0.41	0.71	0.37	0.60	0.84
Credit service used (yes = 1)	0.84	0.57	0.56	0.73	0.63
Households participated in crop rotation (yes = 1)	1.05	0.57	0.50	0.60	0.76
Households participated in erosion prevention (yes = 1)	0.34	0.98	0.85	0.61	0.7
Households head's literacy rate (yes = 1)	0.4	0.41	0.02	0.73	0.80

Source: Authors' computation from SFA.

4. CONCLUSIONS AND IMPLICATIONS FOR POLICY

The study has come up with the following conclusions. Firstly, farmers can increase the output level of those crops considered by improving efficiency and technology adoption. This study revealed that 59% of households were inefficient. Therefore, TC and TE are the major drivers of TFP growth of those considered crops. The technical inefficiency effects were significant, and the TE rate is estimated to gradually increasing over time. This study mainly indicated that farmers increase the output level of crops with the same level of inputs by improving efficiency and technology adoption.

The average estimated TE for crops considered in the study area ranges from 0.036 to 0.79 with the mean TE of 0.41. This value indicates that most households are not technically efficient in producing crops in the study area. This study implied that TC in the production of major crops increased by 22%. According to the findings of this study, improving the use of techniques by farmers should be encouraged. Providing training on production technologies, land conservation, and establishing experience sharing platforms will be of much relevance to enhance the capacity of farmers. Improving supply of farm equipment and other related facilities in small-scale irrigation activities and water harvesting should be a policy direction.

A platform for regular agricultural information flow between extension workers and farmers that has valuable insight to share best experiences should be incorporated in interventions targeting farmers. Furthermore, organic fertilizer use should be a policy priority by the government through the extension service. Finally, focusing on the drivers of productivity are input use, the technology adoption practices, and engagement in extension packages to improve TFP.

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CHAPTER FOUR

HETEROGENEITY, AND TRANSIENT AND PERSISTENT PRODUCTION EFFICIENCIES OF MAJOR CROPS IN SOUTHERN ETHIOPIA[1]

ABSTRACT

Agricultural productivity is a cornerstone for the economy of Ethiopia as it ensure rural transformation. However, the increment of productivity of crop has slow progress. Hence, this study has been undertaken to separate farm heterogeneity, short-run and long-run inefficiencies of productivity in southern Ethiopia. The study used the models of decomposing technical efficiency through various techniques like 4-random error components of SF panel data models to distinguish between time-invariant farm-heterogeneity, persistence, and short-run inefficiencies. Thus, models used for the analysis have shown different estimates of overall efficiency levels. Fixed-effect and Kumbhakar-Heshmati models were not made to separate unobserved persistent efficiency from farm-heterogeneity efficiency. The estimated efficiency by the Kumbhakar-Lien-Hardaker model (0.4449) is significantly higher than the mean of the fixed-effect model with much lower variations in Southern Ethiopia. Mean transient efficiencies gleaned from true-fixed-effect, consistent true-fixed-effect, and Kumbhakar-Lien-Hardaker models become nearly equal except, the Kumbhakar-Heshmati model indicated that farmers faced severe persistent productivity inefficiency problems. Average TC in 2011/12 was 20.67% and declined much more to 9.44% and 5.82% in 2013/14 and 2015/16, sequentially. According to the estimation of overall technical efficiency, it is possible to capture about 39% to 99% of the untapped production in the crop subsector of Southern Ethiopia. Thus, the policymakers should pinpoint the causes of inefficiencies separated in the time factors to improve the productivity of considered crops in the study area.

JEL Classifications:

Keywords: Developing Countries, productivity, persistent, transient inefficiency, southern Ethiopia.

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1. INTRODUCTION

Among the dominant sources for improving agricultural output; agricultural input use, climate conditions, and other location-specific constituents; technologies of farms and best agronomic practices are determinant. As acknowledged by Antwi David (2020), the classical definition of productivity is a measure of how efficiently inputs are combined to produce maximum outputs. However, productivity growth is sub-optimal in Africa compared with performances in Asia, America, and Europe. Thus, agricultural productivity growth in SSA remains slowly moving up, albeit some studies had predicted some degree of recovery in productivity growth after the mid-eighties (Pisulewski, 2019).

Though the Ethiopian agricultural sector averagely accounts for 36.3% of GDP in 2015/16, it has ample arable land, an abundant labor force, and diverse agro-ecological zones. However, growth depends on resource use TE, and TELC. Conceptually, TE describes how a producer can produce maximum feasible output using available inputs (Goshu *et al.*, 2019; Tenaye, 2020).

Chiona *et al.*, (2014) indicated that long-run inefficiency varies across farms due to institutional and statutory environmental facts. While, short-run inefficiency changes because of shocks associated with TC, human capital, and learning-by-doing. Evaluation of long-run and short-run inefficiency separation of unobserved heterogeneity effects have the reverse orientation on promoting efficiency (Colombi *et al*., 2014; Kumbhakar *et al.*, 2015; Adom *et al.*, 2020).

Above all, on average, 79% of land and 85% of grain crop production was covered by cereal crops in a slight improvement in the TE in Ethiopia for the last decade (Hvits and Christine, 2016). There are also conditions in which inefficiency never changes over time: the existing quality of soil, farm water sources for irrigation, the managerial ability of farm, no shift in the farming system stand amongst many. However, conditions in which inefficiency can change as time change: inefficiency caused by the natural hazard, insufficiency of technologies, ignorance for TC. Moreover, the distinction between the persistent and residual components of inefficiency is because they have different policy implications (Heshmati et al., 2018; Agasisti *et al.*, 2019).

On the other hand, panel data in the SPF models have several potential advantages over simple cross-sectional data. Panel data can offer consistent estimators of farm inefficiency and make specific distributional assumptions regarding one-sided error terms associated with inefficiencies (Kathuria, 2011; Colombi *et al.*, 2017; Lai *et al*., 2018).

Against the above discussion, the pivotal research question of this study is distinguishing sources of inefficiency that is elucidated by the objectives of ensuring the practical application of recently developed models on the selected crops in SE: Teff[1] (*Eragrostis*), wheat (*Triticum*)**,** maize (*Zea Mays*), barley (*Hordeum Vulgare*), and sorghum (*Sorghum Bicolor*). Therefore, the objectives of the article presented as follows: first, describing the empirical and theoretical concept of the issues. Next, the article presents the data sources and the models adopted for analysis. Then, the results of the study followed by a nuanced discussion presented. Finally, the article concluded by providing plausible recommendations for practitioners and policymakers.

1.1. Limitations of the Study

Though this study is done based on strongly balanced panel data, data is within the short period panel. The FE model has a limitation of creating bias when the data characterized by a small number of panels but, the degree of bias was lessened by increasing the number of households across the survey years (Treiman, 2014). Moreover, as suggested by (Longhi and Nandi, 2014), systematic measurement errors are expected limitations across the season. However, the power of panel data depends on the reliability and validity of the information it contains (Hill et al., 2020).

2. TIME-INVARIANT AND VARIANT INEFFICIENCY: CONCEPTS AND MEASUREMENT

The panel data controls the individual heterogeneity, high variability, less collinearity between variables with more degrees of freedom and efficiency. Therefore, there are factors in which inefficiency never changes over time: the existing quality of soil, farm water sources for irrigation, no shift in the farming system is called persistent inefficiency. However, factors of

[1]**Teff** is the staple-small size local cereal originated from Ethiopia.

transient inefficiency are natural hazards, inaccessibility/insufficiency of technologies, and ignorance of TC (Alemu and Bishaw, 2015; Agasisti et al., 2017).

Furthermore, applying a single-stage SF model helps to appropriately separate the inefficiency effects as an explicit function of individual-specific variables plus random error which can overcome the problems of inconsistencies. Thus, it allows inefficiency parameters vary across time in different manner and approves a high predictability across farms. However, interpretations of both terms commonly time-related (Colombi et al., 2017; Lai *et al*., 2018).

3. RESEARCH DESIGN AND METHODOLOGY

3.1.Dataset

The regional heads, three Zonal, and district office heads were selected as KII, purposively. The EAs with two FGDs holding ten households were chosen purposively. The qualitative data was collected through semi-structured interviews, FGDs, and KII. The reason was to supplement the quantitative data to analyze the topic. Inclusive questionnaires of household demographic and agricultural information from ESS data sets were used.

In the data management, 2,187 households balanced panel data created for SNNPR as the secondary data. However, some of the missing indicators of productivity of considered crops: soil fertility, the slope of plots, and land tenure status, especially in (2011 and 2013) datasets. Aggregation of those major crops valued in three steps. First, the conversion of local units of measurement was done in a standard measure (Kg).

Conversion factors, prepared by the CSA at the *Kebele* (*Kebele* is the most diminutive administrative structure next to the district) level unit prices was collected. Finally, the value of production is generated by multiplying the average unit price at *the Kebele* level held. Next, monetary values by using the unit price of production were collected. Then, the monetary value of production created by multiplying the mean unit price at the village level and the quantities produced. Based on the CF OF CSA, landholdings of the households were converted into standard measure (hectare) (Bachewe, 2009).

As aforementioned, variation in labor use time throughout the panel years brings measurement errors. The labor force calculation was as follows: first, by sorting the age of each household member using the standards in the adult equivalent. Next, the conversion of days to a week and then to the annual level was carried out. Then, based on their category (men, women, and children), the labor forces are obtained through multiplication. The sum of the number of water storage pit; water pump; sickles; hoes; *Mofer* (*Mofer* is one of the farm capital which could be tied with Kenber and pulled by the oxen); *Kenber (Kenber* is also the farm capital used to plow land putting on the heads of oxen with Mofer*);* traditional plow, and modern plow converted. The qualities of the assets owned are expected to increase the risk of measurement errors in the data. Measurement of Livestock ownership in TLUs following as Jahnke (1982) was done.

3.2.Sampling techniques and sample size Determination

The probability proportion technique was executed to select 74 EAs from ten to two households from the sample of 30 AgSS. In all three years (2011, 2013, and 2015), the chosen EAs and the households for strongly balanced panel data collection were remained the same.

3.3.Model specification

As Heshmati *et al.*, (2018) acknowledged four alternative SPF panel data models for estimating long-run and short-run efficiencies dis-aggregating them from time-invariant farm effects. The FE which assumes inefficiency effects to be time-invariant and individual-specific that can offer estimates of long-run inefficiencies was considered as the first model.

The next model is the TFE model proposed by Greene (2005a) that could separate inefficiencies into transient from persistent effects. The third model is the 3-components random errors that estimate long-run and short-run inefficiencies without accounting for heterogeneity (Kumbhakar and Heshmati, 1995). The fourth model is the recently developed 4-component error that measures persistent and transient inefficiency by separating them from time-invariant farm effects and noise (Kumbhakar *et al.*, 2015; Colombi *et al.*, 2017).

3.3.1. The Stochastic Production Frontier Model Specification

Model 1: Fixed-Effect Model treated as long-run inefficiencies

To specify a model with time-invariant inefficiency effect, we treat a time-invariant term to represent long-run inefficiency to obtain:

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \varepsilon_{it} - u_i \qquad (1)$$

This model utilizes the panel feature of the data via, plus it can be estimated when the inefficiency component u_i is a fixed parameter by the FE-model. However, there are critics on the model assumption about inefficiency, individual instinctive ability, and other persistent farm-heterogeneities that seem to be unrealistic, especially for a long panel dataset (Lai *et al*., 2018).

Model 2: True Fixed-Effects Model treated as heterogeneity

The TFE-model by Greene (2005) separately treats time-invariant farm-heterogeneity and transient inefficiency effects.

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \mu_i + V_{it} - \alpha_{it} \qquad (2)$$

Where μ_i are random-effects to capture any time-invariant farm-heterogeneity, not inefficiency α_{it} represents transient inefficiency and V_{it} is a random shock with the following distribution:

$$\alpha_{it} \sim N^+(0,\ \beta_\alpha^2),\ V_{it} \sim N^+(0,\ \beta_v^2), \text{ and } \mu_i \sim N^+(0,\ \beta_\mu^2) \qquad (3)$$

If μ_i is handled as a fixed-parameter that cannot capture inefficiency, the model is considered as a TFE-model. The TFE-model allows inefficiency to be time-variant and controls for farm-heterogeneity to capture by a farm-specific intercept and assumes that inefficiency terms are always transient. Thus, it fails to capture persistent inefficiency (Kumbhakar and Heshmati, 1995).

Model 3: Individual effects treated as persistent inefficiencies

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

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \pi_{it} \text{ Or}$$

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \varepsilon_{it} - \omega_i - \varphi_{it} \qquad (4)$$

Then, this Kumbhakar and Heshmati-model (KH-model) split the error term into three components where ε_{it} captures a random shock; ω_i captures individual-effects as steadfast inefficiency; φ_{it} captures the transient inefficiency component (Lai *et al.,* 2018).

Model 4: Separation of individual heterogeneity from persistent inefficiencies

Finally, the KLH-model decomposes the error term in the production function into four components: the first captured sectors' latent-heterogeneity across farms (μ_i); the second captured transient inefficiency (φ_{it}); the next captured persistent inefficiency (ω_i) while the last ingredient captured random shocks/noise affecting the farm (V_{it}).

Consider the following panel data SPF model based on distributional assumptions:

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \mu_i + V_{it} - \omega_i - \varphi_{it} \quad (5)$$

This model has four components: two of which, $\omega_i>0$ and $\varphi_{it}>0$ are inefficiencies, and the other two are sectorial effects and noise μ_i and $V_{it,}$ respectively.

Thus, multistep procedure:

$$y_{it} = \sigma^*{}_0 + f(X_{it};\theta) + \sigma_i + \varepsilon_{it} \quad (6)$$

This model was disaggregated as follows:

$$\sigma^*{}_0 = \sigma_0 - \mathrm{E}(\omega_i) - \mathrm{E}(\varphi_{it}) \quad (7)$$

$$\sigma_i = \mu_i - \omega_i + \mathrm{E}(\omega_i) \quad (8)$$

$$\varepsilon_{it} = V_{it} - \varphi_{it} + \mathrm{E}(\varphi_{it}) \quad (9)$$

Therefore, σ_i and ε_{it} in Equations 8 and 9 would have zero mean and constant variance, which is evaluated in three steps: Step 1: Since equation (9) is the standard random-effect panel regression used to estimate θ hat, this procedure also gives predicted values of σ_i and ε_{it}, which we denote by σ hat and ε_{it} hat. Step 2: The time-varying inefficiency, $\varphi_{it,}$ was estimated. The predicted values ε_{it} were used from Step 1. Equation (9) assumes V_{it} was distributed across the producers and time (i.i.d) N (0, $\alpha 2_v$) and φ_{it} is N^+ (0, $\alpha 2_\varphi$), which means E (φ_{it}) = ($\sqrt{2}/\ \pi\alpha 2_\varphi$), and leaving the variation among the true and predicted values of ε_{it}. This procedure gives a prediction of the residual inefficiency components φ_{it} hat. Step 3: The final step, $\boldsymbol{\omega_i}$ were estimated in the same fashion to step 2 and step 1 as the best linear predictor. Equation (8) assumes μ_i and ω_i were distributed across the producers (i.i.d), N $(0, \alpha 2_{\mu})$ and N+ $(0, \alpha 2_{\varphi})$, respectively.

Besides that, by using E $(\varphi_{it})=(\sqrt{2}/\ \pi\alpha 2_{\varphi})$, the standard normal-half-normal SPF model crosses the producers and obtained estimates of the persistent inefficiency components, ω_i. Persistent TE estimated from = exp($-\omega_i$). The variables included in the model and their expected signs are presented in Table 4.1. The aggregate output of major crops is the dependent variable that was assembled from the works of literature discussed in the first portion of the study.

Table 4.1. Variables used for the Estimation of major crops Output

Description	Expected Sign
Amount of seeds consumed	+
Amount of fertilizer consumed	+
Landholding's by the households	+
The labor force at household	+
The number of plowing oxen	+
Age of the household's head	-
Access for Credit service	+
Sex of the head of the household	+

Source: Developed Based on Review of Literature.

4. RESULTS AND DISCUSSION

4.1.Descriptive Statistics of Stochastic Production Frontier

Teff (*Eragrostis*), wheat (*Triticum*), maize (*Zea Mays*), barley (*Hordeum Vulgare*) and, sorghum (*Sorghum Bicolor*) are considered as major crops in SNNPR (Hvits and Christine, 2016). The bulk of production increased due to an increment in the factors of production, except for sorghum. Variation of the output to the variation in the use of inputs is attributed. More specifically, 2011/12 as the base year, the average growth rate (AGR) of maize production showed a slight increment from 9.79% in 2013/14 to 11.17% in 2015/16 (Table 4.2).

Table 4.2.The Average Growth rate of Volume of Production of Major Crops

Major Crops	The average Growth rate of crops is %	
	2013/14	2015/16
Barley	53.61	37.41
Maize	9.79	11.17
Sorghum	-26.24	-31.97
Teff	41.28	30.23
Wheat	29.79	25.08

Source: Authors' estimation.

About 15.22% increment of land coverage from 2011/12 to 2013/14 declined by 10.38% in 2015/16. Therefore, it is possible to argue increment in the bulk of production of considered crops mainly comes from the area expansion in the study area (Table 4.3). According to the qualitative data, the needs for the fertilizer were fluctuated due to the repayment problems and mismatch between the demands and supply of smallholder in SNNPR. It contradicts the findings (Goshu *et al.,* 2019). However, it is consistent with the study of (Taffesse *et al.*, 2012).

There was a decline in the growth rate of fertilizer used and land size covered by considered crops. There was a decline of land coverage by 3.06% for the considered crops from the 2013/14 to 2015/16 production period. Similarly, the growth rate of fertilizer used by households had dwindled by 0.52% (Table 4.3).

Table 4.3. Mean values and Average Growth rate of Households Input-Output data used in Stochastic Production Frontier (2011-2016)

Variables	2011/12	2013/14	2015/16	AGR in %
Amount of fertilizer used	71.56	61.64	66.8	-0.52
Households' seed used	2.90	14.99	19.69	57.14
Value of farm-capital	4.31	4.92	5.04	5.88
Labor force	319.55	388.62	412.37	10.4
Area cultivated	0.92	1.07	0.95	-3.06
Number of plowing oxen	0.82	1.15	1.14	9.62
Real value of output produced	1,035.09	1,092.4	1,240.78	10.51

Source: Authors' calculation.

4.2. Hypothesis tests on the Estimation of Stochastic Production Frontier

Though the logarithmic values of inputs and aggregated crop output were used in estimating the models, the logarithmic values of some variables resulted zero which could become undefined. Thus, the variables with zero values were changed to nearly zero (0.0001) value before transformation. It was consistent with the findings of Wassie (2014). Various statistical tests were performed for the parameter estimates of the production frontier and the factors that are presumed to affect the efficiency of producers of major crops as well as the validity of the model before the analysis.

Wald tests are the commonly used parametric test for testing the H_0 of either no or constant inefficiency. It means, the variance of the one-sided process is not zero, and the explanatory variables are jointly significant in explaining the dependent variable. Thus, inefficiency effects are present in the model. Since γ took the value between 0 and 1, the H_0 is rejected at $p<0.001$. Besides, the eta (η) is different from zero, H_0 is rejected at $p<0.001$. Alternatively, this is to test whether the SPF function is more appropriate than the conventional one. However, if the H_0 is not rejected, the SPF function could be equivalent to the conventional one.

Moreover, restrictions for no unobserved heterogeneity, no observed heterogeneity, and the assumption of constant inefficiency over term for technical inefficiency are rejected at the 1% level of significance. Therefore, unconstrained TE, a time-varying, time in-varying, and half-normal distribution for inefficiency were estimated (Table 4.4).

Table 4.4. Properties of Wald test Statistic

Hypotheses	**LL H_0**	**LL H_1**	**Wald Test Statistic**	**p-Value**
No unobserved heterogeneity	H_0: Var (u_{it})=0	H_1 :Var (u_{it})≠0	578.55	0.000
No observed heterogeneity	H_0: $\alpha_1 = \alpha_3 = \cdots \alpha_6 = 0$	H_1 :$\alpha_n \neq 0$	1020.70	0.000
Constant inefficiency	H_0 : eta(η)=0	H_1 : eta(η)≠0	637.87	0.000

Source: Author's calculation.

Furthermore, the robustness check under alternative specifications of the models performed. By adding or removing explanatory variables, the robustness checks were performed. According to

Table 4.5, the Ho is rejected at p<0.001. There is half-normal distribution. Thus, the Ho for the test of no half-normal distribution is rejected at p<0.001.

The likelihood-ratio test statistic λ = -2{log [Likelihood (Ho)]–log [Likelihood (H_1)]} has approximately a chi-square distribution ($\chi 2$), distribution with q equal to the number of parameters assumed to be zero in the H_0; it is compared with the critical values of ($\chi 2$) and decided between the two models (Table 4.5) (Chiona *et al.*, 2014).

Table 4.5. Generalized Likelihood-ratio tests for the Parameters of Stochastic Production Frontier and Inefficiency Factors

Hypotheses	LL H_0	LL H_1	Test Statistics*	Critical Value	Decision
Constant return-to-scale Ho: $\beta 1 = \beta 2 = \beta 3 = \beta 4 = \cdots = \beta 6 = 0$	-3421.55	-3411.38	20.51	20.34	Reject H_0
μ is not half − normal distribution (H_0: $\mu = 0$)	-3421.01	-3403.62	34.78	22.46	Reject H_0
No inefficiency (H_0: $\gamma = 0$)	-3436.92	-3403.62	66.6	13.82	Reject H_0

Note LL stands for log-likelihood. Source: Authors' estimation.

4.3.Estimates of Technical Efficiency

Consistent with the findings of Adom *et al.*, (2020) study, according to KLH-model, about 27.4% of TE possibly used to produce maximum aggregate crops in SE. Comparatively; the estimated overall TE in the KLH-model is higher than the values obtained under the KH and TFE models. Moreover, results from the KLH-model provided time-varying TE that reflects the overall/transient efficiencies. Thus, the other model's results illustrated significant variations from KLH-model are sensitive to the model's specifications (Table 4.6).

Consistent with the findings of (Berisso and Heshmati, 2020), the estimation of the KLH-model for mean persistent efficiency was 0.4449 but FE and KH-models underestimated. However, the mean transient efficiency values obtained from TFE, CTFE, KLH, and KH-models are 0.61, 0.62, 0.62, and 0.43 respectively, indicated that producers faced severe persistent productive inefficiency problems in SE. The average persistent productive inefficiency is 79%, designating that the study area stayed in long-lasting challenges in inefficiency. Therefore, it is possible to argue that mediocre, there was 43.24% of un-captured household's time-varying TE in the production processes (Table 4.6). It is consistent with (Heshmati *et al.*, 2018) findings. Furthermore, the qualitative data indicated that sources of persistent inefficiency: no shift in the farming system; failure in the farm management; existing soil quality; the farm has no irrigation water naturally in the study area. However, sources of the transient inefficiency were erratic rainfall distribution, land degradation, soil erosion, lack of cropping techniques; inaccessibility of inputs and technology; lack of information, trial and error process in unknown situation in the study area.

Table 4.6.Estimate of Technical Efficiency

TE	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Overall TE				
FEM_TFEM	0.0679536	0.0442676	0.00000105	0.9999991
FEM-CTFEM	0.068619	0.0740559	0.0000009	0.9999991
K-L-H	0.2741433	0.0646918	0.0000419	0.7867339
K-H	0.0309569	0.0132422	0.0003802	0.8250605
Persistent TE				
FEM	0.1113977	0.1202241	0.0010558	1
K-L-H	0.4449917	0.1766847	0.0483087	0.7867345
K-H	0.0722698	0.0708844	0.0215765	1
Transient TE				
TFEM	0.6100091	0.3682091	0.0009933	0.9999989
CTFEM	0.6159822	0.3658393	0.0008563	0.9999991
K-L-H	0.6160639	0.3661426	0.0008673	0.9999992
K-H	0.428353	0.1868145	0.0176221	0.8250605

Note: CTFEM (consistent TFE-Model). Source: Authors estimation.

4.4.Estimated Marginal Elasticity

Consistent with the findings (Adom *et al.*, 2020; Tenaye, 2020), estimates of production elasticity indicated that each input contributed significantly to the considered crop production. However, the magnitude of the elasticity varies across models. Therefore, as land coverage increases by 1%, the estimated increment in the outputs of considered crops were by 0.31% and 0.17% in both the FE and TFE models, respectively (Table 4.7).

In the same fashion, 1% increment of land coverage of major crops, the KH and KLH-models estimations of outputs are by 0.12% and 0.21%, respectively, in the study area. Increase in the labor force by 1%, increased production of considered major crops by 0.03% in the FE-model but 0.04% in TFE, KH, and KLH-models. Moreover, a 1% increase in fertilizer use has an estimation of 0.03% improvements of considered crop output in both FE and TFE-models yet, the magnitude and effect on those crops were the same (0.04%) in both KH and KLH-models during the survey years (Table 4.7).

The marginal effects of the number of oxen have the same magnitude in the products of considered crops in FE and TFE models in the study area. In other words, a 1% increase in the number of oxen increased the aggregate major crops by 0.07% in both FE and TFE models during the survey years. However, a 1% increase in the number of oxen is estimated to improve 0.06% and 0.12% outputs of major crops in KH and KLH-models, respectively. However, the magnitude of marginal elasticity in both FE and KH-models is lesser than TFE and KLH-models in the analysis. An increase in 1% in the use of seed was estimated to increase the production of considered crop outputs by 0.04% and 0.03% in FE and KH-models, respectively (Table 4.7).

Table 4.7.Estimated Marginal Elasticity of Cobb-Douglas Stochastic Frontier Analysis

Variables	**FEM**	**TFEM**	**KH**	**KLH**
	Estimate	**Estimate**	**Estimate**	**Estimate**
Logarithmic value of land_size	0.31***	0.17***	0.12***	0.21***
	(0.063474)	(0.00173)	(0.0356)	(0.035646)
Logarithmic value of labor force	0.03***	0.04***	0.04***	0.04***
	(0.008048)	(0.0003)	(0.0064)	(0.065953)
Logarithmic value of oxen	0.07***	0.07***	0.06***	0.12***
	(0.008139)	(0.0006)	(0.00695)	(0.072786)
Logarithmic value of fertilizer used	0.03***	0.03***	0.04***	0.04***
	(0.006448)	(0.0004)	(0.00503)	(0.04149)
Logarithmic value of seed used	0.04***	0.05***	0.03***	0.05***
	(0.007281)	(0.0005)	(0.00599)	(0.05155)

*Denote: Coefficient) standard errors under parentheses. ***, ** and * denote 1%, 5% and 10% statistical significance level. Source: Author's Estimation.*

4.5.Estimates of Technical Efficiencies across Zone in Southern Ethiopia

In comparison, the aggregate persistent TE is lower than the transient one in SE, confirming that inefficiency varies from zone to zone between zones and household to household within the zone during the survey years (Table 4.8). As the qualitative data indicated that the variability in the determinant factors of efficiency, some of the central zones: Gurage, Sidama, Hadiya, Kambata Tamibaro, Gedeo, Wolayita, Gamo Gofa, and Silti zones have better performance of producing those crops than others. However, based on the quantitative data estimation, the periphery zones like Derashe and Burji Special were better than those in the centers.

A comparison of TE between zones within SE revealed some extent of heterogeneities. Following the findings of Berisso and Heshmati (2020), based on TFE and KLH-models, the top-five good performing zones were Derashe (0.687 and 0.689), Burji Special (0.683 and 0.667), Gurage (0.656 and 0.651), Sidama (0.645 and 0.645), and Woliata (0.638 and 0.645). It is consistent with the findings of Hvits and Christine (2016). Therefore, Derashe emerged as the best performer followed by Burji Special, Gurage, Sidama, and Woliata, indicated that the productivity within these zones improved significantly during the survey (Table 4.8).

Table 4.8.Mean Summary of Efficiency Measures in all Models by Zones

	PTE			TTE			
Zones/Areas of SE	**FEM**	**KH**	**KLH**	**TFEM**	**CTFEM**	**KH**	**KLH**
Gurage	0.120	0.053	0.504	0.656	0.651	0.487	0.651
Hadiya	0.082	0.068	0.422	0.606	0.616	0.418	0.615
Kambata Tamibaro	0.058	0.074	0.376	0.601	0.606	0.363	0.605
Sidama	0.263	0.036	0.624	0.645	0.645	0.611	0.645
Gedeo	0.216	0.044	0.569	0.633	0.630	0.546	0.632
Wolayita	0.076	0.068	0.408	0.638	0.644	0.398	0.634
South Omo	0.038	0.097	0.310	0.553	0.649	0.310	0.650
Sheka	0.242	0.055	0.550	0.635	0.637	0.539	0.638
Kefa	0.033	0.103	0.326	0.611	0.608	0.290	0.609
Gamu Gofa	0.046	0.100	0.355	0.607	0.608	0.332	0.610
Bench Maji	0.129	0.263	0.520	0.611	0.621	0.510	0.621
Yem	0.024	0.216	0.248	0.529	0.531	0.212	0.531
Amaro Special	0.110	0.051	0.511	0.578	0.587	0.472	0.587
Burji Special	0.028	0.169	0.272	0.683	0.666	0.216	0.667
Konso Special	0.069	0.081	0.468	0.581	0.577	0.379	0.577
Derashe	0.137	0.062	0.523	0.687	0.688	0.457	0.689
Dauro	0.034	0.097	0.321	0.601	0.605	0.299	0.606
Basketo	0.177	0.048	0.552	0.592	0.617	0.546	0.615
Konta	0.048	0.104	0.350	0.602	0.581	0.334	0.581
Silti	0.084	0.062	0.438	0.573	0.583	0.441	0.583
Alaba	0.089	0.061	0.427	0.532	0.549	0.445	0.549

Denote: PTE (persistent technical efficiency), TTE (transient technical efficiency)

Source: Author's computation.

Furthermore, by using density plot, it was possible to find efficiency components in different models. These density plots show that the distribution of persistent efficiencies in the FE and KH-models was identical and except for some values in the upper tail. In the persistent TE, most households had low efficiency in SE. However, in the KLH-model, there are the highest steadfast efficiency scores with a mean value of more than 44% (Figure 4.1).

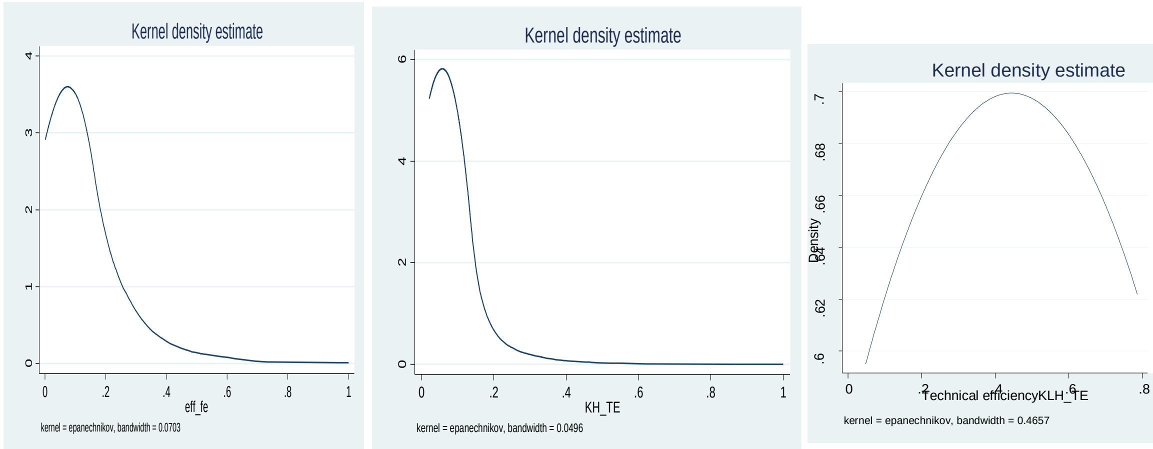

Figure 4.1. Distribution of persistent efficiencies across models

Source: Author's computation.

As the parts of overall efficiency, the spread of the transient efficiency was significantly higher than that of the persistent component. Therefore, the persistent inefficiency is a challenge compared to the other inefficiency in SE (Figure 4.2).

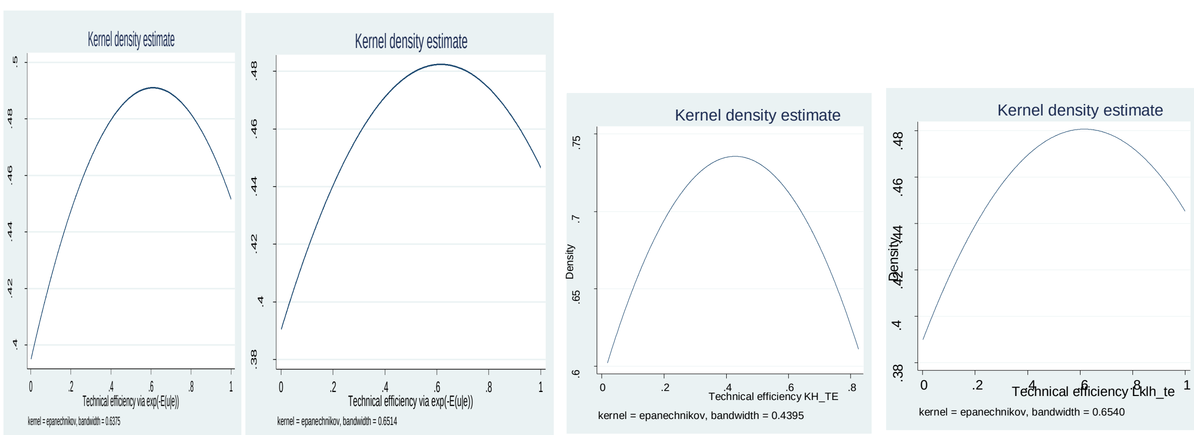

Figure 4.2. Distribution of transient efficiencies across models

Source: Author's computation.

4.6.Total Factor Productivity, Returns to scale and Technical Changes by Preferred True Fixed Effect Model

Consistent with the studies of (Colombi *et al.,* 2017; Keith *et al*.,2017), the TFE-model found unobserved household/farm-specific heterogeneity in producing values of overall/transient efficiencies that were preferred to separate inefficiencies across individual and time. Therefore, in TFE-model, TE increased from 63.82% to 72.72% from 2011 to 2013, while it declined to 56.62% in 2015. The diminishing return to scale was from 87.05% to 77.53% in 2011/12 to 2013/14 and declined more to 62.8% in 2015/16 (Table 4.9).

Moreover, the average TC in 2011 was 20.67% and declined much more to 9.44% and 5.82% in 2013 and 2015, respectively, indicated that households were less sensitive to the newly invented technologies. Thus, uptake of technological practices for the production of considered crops through intensification has decreased in southern Ethiopia (Table 4.9).

Table 4.9.Mean Summary of Components of Productivity Scores

Variables	**2011**		**2013**		**2015**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Technical Efficiency	0.6382	0.3502	0.7272	0.3276	0.5662	0.3538
Return to Scale	0.8705	0.2287	0.7753	0.2278	0.6280	0.2280
Technical Change	0.2067	0.1415	0.0944	0.1485	0.0582	0.1246
Total Factor of Productivity	5.6167	1.3370	6.1813	1.1799	5.9368	1.2409

Source: Author’s Computation.

5. CONCLUSIONS

The efficiency estimated in KLH-model is higher than the values obtained under the other models. Thus, the results from the KLH-models provided time-varying TE that reflects the overall efficiencies indicating the sensitivity of the model’s specified. The findings also suggested that 72.6% overall inefficiency exists in the yield of major crops. The estimation of the KLH-model for mean persistent efficiency was 0.445 only FE and KH-models underestimated inefficiency values.

Moreover, it is possible to argue that mediocre, there is 43.24% of un-captured household's time-varying TE in the production processes of those considered crops in SE.

The results show differences in inefficiency at the zone level during the survey years, confirmed that Derashe performed well followed by Burji Special, Gurage, Sidama, and Woliata. The estimation of total efficiency implied that improving efficiency in the agricultural sector, Southern Ethiopia can capture about 39% to 99% of the un-captured or untapped maximum considered crop production. Finally, this study pinpoints the policy implication of having a separate national plan on the sources of inefficiencies based on time. The local government has to work on the persistent inefficiency sources of the region.

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CHAPTER FIVE

IMPACT OF TOTAL FACTOR PRODUCTIVITY GROWTH ON RURAL POVERTY IN SOUTHERN ETHIOPIA[1]

ABSTRACT

In Ethiopia, the poverty-reducing potential of agricultural productivity is increasing faster than the population. Thus, this study was undertaken to examine the impacts of productivity growth in rural poverty. The panel data estimated the Cobb-Douglass stochastic production function with the time-varying decay models, and Foster, Greer, and Thorbecke indices on the Living Standard Measurement Survey (2011, 2013, and 2015) data of World Bank. Inputs determined the aggregate output significantly at 1 per cent. Variation in the inefficiency term explained 46.4 per cent of the total variance in the composed error term. The average productivity of considered crops was 6.19 per year in the study area. Though there was 41% efficiency in the productivity of considered crops, there was poverty in the study area. The percentage of households below the poverty line (Head Count Index) declined from nearly 19.28% in 2011/12 to 16.36% in 2013/14 and 13.91% in 2015/16. Households were efficient but the poor in the study area. However, further analysis is necessary to make more tangible claims about the impact of growth productivity on poverty since we only focused on the direct effects of increasing considered crop farm productivity.

Keywords: Productivity Growth, Efficiency, Poverty Reduction, Southern Ethiopia, crops.

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1. INTRODUCTION

Rural poverty is a multidimensional concept that includes the deprivation of agricultural productivity, basic needs, education, and health (Manaliliby, 2011). Rural-poverty response to productivity growth differs from country to country. Factors in determining the countrys' response to poverty depend on the presence or absence of productivity gains, the sector composition of improvement of its labour intensiveness, the extent of agricultural input use and, technology adoption (Guan *et al.,* 2015; Diriba et al., 2020). Agriculture in SSA is more subsistence and concentrated in low-value food crops accounting for more than 2/3 of agricultural output (Spielman *et al*, 2010; Ndulo, 2011; Addia *et al.,* 2014; Ogundipe et al., 2016).

As Chongcharoentanawat *et al.,* (2016) acknowledged that 29.6% of the total population of the country lives below the national poverty line, indicating that poverty is more prevalent in rural (30.4%) than urban areas (25.7) in Ethiopia. However, crops: teff, maize, sorghum, barley, and wheat are core crops and significant contributors to the country's economy (Hvits and, C. (2016). The aforementioned implies that productivity growth directly affects the welfare of the bulk of rural poor and the level of TE of crop farming (Demeke *et al.,* 2011; Gebreegziabher *et al.,* 2020).

Thus, poverty due to low crop productivity growth has been a long-standing challenge with uneven progress across Africa (McGuire, 2015). Analysis of productivity growth over time and productivity differentials between countries, regions, and farmland are critical issues in improving the TE of agricultural development (Carletto, 2013). Therefore, substantial improvements in efficiency and high technology adoption rates are needed to be parallel with expanding demand for economic growth in Africa (Rao *et al*., 2004; Po-Chi, *et al.*, 2008).

However, the African model of crop production growth is significantly different from that of Asia or South America. In Asia, growth was driven by intensification whereas, in South America, it was due to significant improvement in labour productivity and efficient adoption of new farm technology and enhancing its efficiency. By contrast, growth in Africa farm output has accrued mainly from area expansion and intensification of cropping systems (Brink and Eva, 2009; Gray *et al.,* 2011; Ajayi et al., 2020).

On the other hand, the methodology examines the linkages between agricultural productivity and rural poverty in Ethiopia using the static and dynamic framework of productivity and rural poverty. Moreover, the economic theories suggest per capita expenditure is the best indicator of welfare but presupposes that households maximize a continuous utility function defined over commodities (Sahn et al., 2000; Bigsten and Shimeles, 2008; Taffese *et al.*, 2012). However, there are two approaches in poverty analysis: the welfarist and non-welfarist approaches. Developing countries show an inverse relationship between productivity efficiency and poverty in rural people (Adeyemi, 2017; Diriba *et al*., 2020).

The definition of poverty within the welfarist method is lack of command over commodities, measured by low income or/and consumption that are imperfect proxies for utilities. The welfarist approach also agreed well-being, consumption, or income indicators often adjusts differences in household's need, size, and demographic structures as well as postulating a poverty line, and identification of the poor from the non-poor can be made (Foster, 2009; Duclos, 2010; McGuire, 2015; Adeyemi, 2017; Pernechele et al., 2018).

There are three reasons for considering consumption as a better indicator of well-being. The first is it directly measures the flow of utility-producing inputs. The second is that it approximates permanent economic position better than current income since income only measures the potential to acquire those inputs. Since consumption manifests actual and not potential flow, income is only a proxy measure of poverty because it only approximates consumption. Thirdly, the reason for the price differences of the same item drives a wedge between distributions of income and consumption (Romina *et al*., 2018; Taffesse *et al.*, 2012; Cervantes-Godoy, 2010).

Against the backdrop of the fore-noted problems, this research examines the impact of the total factor of productivity on rural-poverty in Southern Ethiopia. Thus, the implication of this study significantly informs policymakers. Moreover, it strengthens the existing model, theory, and knowledge based on empirical evidence. Therefore, the remainder of the article presents as follows: first, the empirical and theoretical literature on the concept of TE and TELC presentation followed by the description of panel data SF models. Secondly, the article presents the data sources and methods of the data collection and the model adapted to examine the data.

Then, the results of the analysis followed by a nuanced discussion presented. Finally, the article concludes by providing plausible policy implications.

2. RESEARCH DESIGN AND METHODOLOGY

2.1. Dataset

The specific primary data is collected by employing semi-structured interviews, FGD, and KII techniques. The regional, three Zonal, and three districts Agriculture Natural Resources Development office heads were selected as KII, purposively. Two FGD from each of the EAs holding ten households were selected, purposively. The reason was to supplement the quantitative data. Inclusive questionnaires of household demographic and agricultural information from ESS datasets were used for this study.

In the data management, 2,187 households balanced panel data created for SNNPR as the secondary data. However, some of the missing indicators of productivity of considered crops: soil fertility, the slope of plots, and land tenure status, especially in (2011 and 2013) datasets. Aggregation of those major crops valued in three steps. First, the conversion of local units of measurement was done in a standard measure (Kg).

Conversion factors, prepared by the CSA at the *Kebele* (*Kebele* is the most diminutive administrative structure next to the district) level unit prices was collected. Finally, the value of production is generated by multiplying the average unit price at *the Kebele* level held. Next, monetary values by using the unit price of production were collected. Then, the monetary value of production created by multiplying the mean unit price at *the village* level and the quantities produced. Based on the CF OF CSA, landholdings of the households were converted into standard measure (hectare) (Bachewe, 2009).

As aforementioned, variation in labor use time throughout the panel years brings measurement errors. The labor force calculation was as follows: first, by sorting the age of each household member using the standards in the adult equivalent. Next, the conversion of days to a week and then to the annual level was carried out. Then, based on their category (men, women, and children), the labor forces are obtained through multiplication. The sum of the number of water storage pit; water pump; sickles; hoes; *Mofer* (*Mofer* is one of the farm capital which could be tied with Kenber and pulled by the oxen); *Kenber (Kenber* is also the farm capital used to plow land putting on the heads of oxen with Mofer*);* traditional plow, and modern plow converted.

The qualities of the assets owned are expected to increase the risk of measurement errors in the data. Measurement of Livestock ownership in TLUs following as Jahnke (1982) was done.

2.3.Sampling techniques and sample size Determination

The probability proportion technique was executed to select 74 EAs from ten to two households from the sample of 30 AgSS. In all three years (2011, 2013, and 2015), the chosen EAs and the households for quantitative data collection were remained the same.

2.4.Model Specification

The TVID model with deterministic and stochastic-components were used to estimate households' efficiency on the basis of assumption that unobserved individual-error as random and a deterministic function of time-dummies (Kuosmanen, 2009; Colombi et al., 2014). These models were selected over the other panel data models of the production function as it drops the entire incidental parameters problem in the analysis (Kumnhakar et al., 2014).

Thus, this model fixed inefficiency for a given individual and changed it over time and across individuals. (Lai *et al.*, 2018). Thus, the study employed specific SF parametric approaches of SPF and deterministic models to measure TE and TC with considered crops. The models were selected over the other panel data models of the production function due to it drops the entire incidental parameters problem in the analysis. Thus, this model fixed inefficiency for a given individual and changed it over time and across individuals. The parametric deterministic production frontier is presented as follows:

$$y_{it} = f(X_{it};\theta) * \exp(-\mathrm{u}) \qquad (1)$$

Where Y_{it} is the scalar output of a producer, $f(X_{it};\ \theta)$ is the deterministic part of SPF with technology parameter vector θ to be estimated, $\mathbf{X} = (\mathbf{X}_1, \ldots X_n) \geq 0$ is an input vector, $\mathbf{t}$ is a time trend serving as a proxy for TC, and $u \geq 0$ represents output-oriented technical inefficiency. From this production frontier, the rate of TC measured as follows:

$$\Delta TC = \frac{\partial \ln f(X_{it};\theta)}{\partial t} \qquad (2)$$

Then, ΔTC would have three chances: being a value greater than, less than, or equal to zero as TC shifts the production frontier up, leaves it unchanged, or shifts it down, respectively. Similarly, the rate of change of TE ΔTE also measured as:

$$\Delta TE = -\frac{\partial u}{\partial t} \qquad (3)$$

Where ΔTE is TE, the inefficiency term ∂u is always between 0 and 1, where ∂u is equal to zero, then production is on the frontier and ΔTE = 1, therefore the farmer is technically efficient. When ∂u is greater than zero, the farmer is technically inefficient (ΔTE<1), since production is below the frontier. In other words, when, ΔTE, would have a value greater than, less than, or equal to zero as technical inefficiency declines, remains unchanged, or increases through time, respectively (Alene, 2010).

$$lnoutput_{it} = \beta_0 + \beta_1\, lnland_{it} + \beta_2\, lnoxen_{it} + \beta_3\, lnseed_{it} + ... + \beta_n\, lnlabor_{it} + \beta_n\, lnfertilizer_{it} + \varepsilon_{it} \qquad (4)$$

$$i = 1...., I \text{ and } t = 1..., T \text{ and } \varepsilon_{it} = V_{it} - U_{it} \qquad (5)$$

Where ε_{it} is composed of error terms V_{it} and U_{it}. V_{it} is a non-negative random variable (inefficiency) term, assumes the distribution as half-normal distribution above zero of the N(μ, σ_u^2) distribution. Error terms of U_{it} and V_{it} are the idiosyncratic and inefficiency components of the composed error term in the same order, ε_{it} of producer i at time t (Kuosmanen, 2009; Kumbhakar *et al*., 2015).

$$u_{it} = \gamma u_i = \{\exp[-\gamma(t - T)]\}u_{it} \text{ and } TE_{it} = E\left[exp(-{}^{u_{it}}/_{\varepsilon_{it}})\right] \qquad (6)$$

Where ϒ is an unknown scalar parameter and T is the last period for which observations for the ith households were obtained? This model assumes that u_{it} decreases, remains constant or increases, as ϒ > 0, ϒ = 0 or ϒ < 0, respectively. Setting ϒ = 0 provides the time-invariant model. On the other hand, ϒ > 0 implies households tend to improve their efficiency over time and vice versa. V_{it} is assumed to be independently and identically distributed. Thus, based on these assumptions, the probability density function of the composite error term ε_{it} and its log-likelihood function is derived for the model using the maximum likelihood estimation technique.

The predicted value of TE for producer i in period t is the conditional expectation of the inefficiency component in the error term.

The TFP was estimated using the control function approach like LP approach (Levinsohn et al., 2003; Van Beveren, 2012; Wooldridge, 2016). The logarithmic transformation was performed in the output variable through time. Cobb–Douglas production-function as follows:

$$lnoutput_{it} = \alpha_0 + land_{it} + seed_{it} + fertilzer_{it} + oxen_{it} + labour_{it} + \text{epsilon\_it} \qquad (7)$$

Where $lnoutput_{it}$ was the log of output, $land_{it}$, $seed_{it}$, $labour_{it}$, $fertilzer_{it}$ and $oxen_{it}$ were the logarithmic inputs that all of were observed. Then, TFP was estimated by predicting the production function estimation method. Moreover, consumption per capita per household (CPCPH) was a good indicator of household welfare and living standards. Thus, it was undertaken by employing real consumption expenditure per capita (RCEPC) or C_{it} to measure rural poverty and to identify the relationship between growth in productivity and rural poverty. A two-step procedure for estimation was estimating the determinants of household real consumption per capita:

$$lnC_{it} = \alpha_i + \beta Prod_{it} + \gamma X_{it} + \varepsilon_{it} \qquad (8)$$

Where lnC_{it} is the natural logarithm of real household consumption per capita of household **i**, α_i is random individual-specific (unobserved) effects, ϒ and β are the vector of parameters to be estimated, X_{it} represents exogenous repressors which serve as a control, $Prod_{it}$ the indicators of productivity of farmers. C_{it} Household used as an indicator of socio-economic variables and other relevant variables. The study used two ways of modeling the econometric analysis: the determinants of C_{it} and the robust fixed-effect model. Second, as acknowledged by several studies, performing a poverty prediction by using static FGT indices of poverty was measured based on C_{it} (Bachewe, 2009; Cervantes-Godoy, 2010; Ajayi et al., 2020; McGuire, 2015)

$$P_{\alpha,t} = \frac{1}{\sum_i^n w_{it}} \sum_{i=1}^{n} \left(\frac{Z-\widehat{C_{it}}}{Z}\right)^{\theta} w_{it} I_{it} \qquad (9)$$

Where, **n** is the number of observations, **Z** indicates the poverty line, $I_{it}= 0$ if $\hat{C}_{it} \geq 1$ Z and 1 otherwise, w_{it} represents household size used as the weight of the i^{th} element. $\boldsymbol{\theta}$ is the poverty aversion parameter which usually takes a value of 0, 1, and 2. When $\boldsymbol{\theta} = 0$, $P_{\alpha,t}$ is the HCI (the incidence of poverty) which measures the proportion of households living below the poverty line.

The $P_{\alpha,t}$ measures the depth of poverty when = 1. It measures the extent to which households fall below the poverty line indicating the poverty gap. It can also be considered as a measure of the minimum cost of eliminating poverty relative to the poverty line. The $P_{\alpha,t}$ is called the Squared Poverty Gap when $\boldsymbol{\theta} = 2$, which measures the severity of poverty. It implicitly puts more weight on those observations that fall far below the poverty line and is thus sensitive to inequality among the poorest households.

Table 5.1.Descriptions of Variables and Expected Signs

Description	Expected Sign
Total Factor Productivity	Positive
Household size	Negative
Dependency ratio	Negative
Livestock ownership in tropical livestock units (TLUs)	Positive
Village level price index	Negative
Any income related to farm (in Birr)	Positive
Sex of the head of the household (1 = male-headed, 0 otherwise	Positive
Age of the household's head	Negative
Distance to nearest markets	Negative
Years of schooling for the head of the household	Positive

Source: Developed Based on Review of Literature.

3. RESULT AND DISCUSSION

3.2.Description of Average Value of Input and Output of Major Crops

There was a slight decline in fertiliser consumption in the 2013/14 survey year compared to that of 2011/12 by 9.85Kg. The cultivated land increment by 15.22% was from 2011/12 to 2013/14 become, declined by 10.38% in 2015/16 in the study area. Therefore, it is possible to argue that the increase in the volumes of the stocks of considered crops is due to area expansion (Table 5.2). In contrast to findings of (Goshu *et al.*, 2019), who argued on the cause of the increment of the output of major crops, but in agreement with (Taffesse *et al.,* 2012) claimed despite the increase in land cultivated during 2010-16 in Ethiopia, productivity increment of cereal crops appeared mainly due to area expansion and, intensification of modern inputs as well.

The labour force employed from land preparation to harvesting periods increased consistently during the survey years. In 2011/12, the average growth rate of the labour force who allocated their time in the production process of crops increased by 21.61%. The labour force growth declined to 14.13% in the 2015/16 production year, and the growth rate of fertiliser used by households is also dwindled by 0.52% (Table 5.2).

Table 5.2.Mean Values and Average Growth rate of Households Input-Output Data in SPF (2011-2016)

Variables	2011/12	2013/14	2015/16	AGR in %
Real value of output produced	1,035.09	1,092.4	1,240.8	10.51
Participation in the extension program (Yes = 1)	0.27	0.45	0.45	15.38
Credit service used (yes =1)	0.29	0.37	0.36	5.88
Prevention of damage of crop by chemical (yes=1)	0.39	0.51	0.53	10.42
Households' participated in crop rotation (yes=1)	0.37	0.40	0.43	7.5
Households' participated in erosion prevention (yes=1)	0.38	0.44	0.47	9.3
Amount of fertilizer used	71.56	61.64	66.8	-0.52
Households' seed used	2.90	14.99	19.69	57.14
Labour force (man-days)	319.55	388.62	412.37	10.4
Area cultivated (in hectare)	0.92	1.07	0.95	-3.06
Number of ploughing oxen	0.82	1.15	1.14	9.62

Source: Authors' calculation.

Though the logarithmic values of inputs and aggregated crop output were used in estimating the models, the logarithmic values of some variables resulted zero which could become undefined. Thus, the variables with zero values were changed to nearly zero (0.0001) value before transformation. It was consistent with the findings of Wassie (2014). Various tests were executed before the analysis.

Wald tests performed for parametric testing of the H0 of no inefficiency. In other words, the variance of the one-sided process assumed zero and explanatory variables were jointly significant enough in explaining the dependent variable. Then, inefficiency effects were present in the model. When H0 takes values between 0 and 1, it might get rejection. Alternatively, it tests whether the SF production function is more appropriate than the conventional one. If the H0 is not rejected, the SF production function would have the same value as the conventional one. Thus, heteroscedasticity might be inherent in the data set. Based on the log-likelihood test, H0 rejected indicated the presence of inefficiency in the production of major crops in the study area.

Estimating by the half-normal distribution SF model and the log-likelihood test made continuous iteration and attached the maximized iteration, which used to calculate the log-likelihood statistics. The likelihood-ratio test statistic $\lambda = -2\{\log [\text{Likelihood (H0)}] - \log [\text{Likelihood (H1)}]\}$ has approximately a chi-square distribution ($\chi 2$), distribution with q equal to the number of parameters assumed to be zero in the H0; it is compared with the critical values of ($\chi 2$) and decided between the two models (Coelli *et al.*, 2005). According to AIC and BIC presented in (1974), a model with the MLE of the parameters which give the minimum of AIC accepted.

3.3. Estimation of Stochastic Frontier Model

The maximum likelihood estimation of parametric time-varying inefficiency Cobb-Douglas stochastic frontier production function is discussed in Table 5.3. Wald test indicated that all the explanatory variables used in the model significantly explained the dependent variable. The value of eta (η) indicated that the level of inefficiency decays toward the base level declining by a factor of 0.04 significantly. This result is consistent with the findings of Abro *et al*., (2014). Production is technically inefficient if it is impossible to produce a sound output with at least one input (Gray *et al.*, 2011; Mastromarco, 2008; Jorgenso, 2018).

All of the explanatory variables maintained the expected sign and were significant. Variation in the inefficiency term explained 46.4% of the total variance in the composed error term. In other words, 46.4% of the variation in the outputs of considered major crops among the households is explained by technical inefficiency. A 10% increment in the number of ploughing oxen, labour force, land size, and fertilizer consumption is estimated to improve the aggregate output of crops by more than 0.61%, 0.37%, 1.18%, 0.41%, respectively. Although the sign of the coefficients' of seed is positive, its elasticity compared to the other explanatory variables is less responsive to the output (Table 5.3). The findings of Goshu *et al.*, (2019) are consistent.

Generally, the elasticity of marginal effects of all inputs used for the estimate indicated an increase in inputs increased the aggregate output of major crops. However, the sum of the value of transformed parameters used for an estimate in the logarithmic form (0.29) indicated that there is diminishing marginal returns to scale in the production processes of aggregate crops during the survey years.

Table 5.3.Results from the Stochastic Frontier Model

Variables	Coefficients	Std. Err.	z-test
Constant	7.0938***	0.13	53.50
Logarithm of area cultivated	0.1176***	0.04	3.27
Logarithm of ploughing oxen	0.0614***	0.01	8.91
Logarithm of fertilizer used	0.0411***	0.01	8.11
Logarithm of seed used	0.0335***	0.01	5.40
Logarithm of labor-force in man days	0.0374**	0.01	5.72
/mu(μ)	0.49**	0.48	1.01
eta(**η**)	0.04**	0.02	2.51
/lnsigma2	0.97***	0.15	6.65
/ilgtgamma	-0.14**	0.32	-0.45
Sigma2($\sigma^2_u + \sigma^2_v$)	2.64	0.39	
Gamma(γ)	0.46	0.08	
sigma_u2(σ^2_u)	1.23	0.38	
sigma_v2(σ^2_v)	1.41	0.06	

Log likelihood = -3394.0797; Wald chi2 (5) = 1020.70; Prob >= chibar2 = 0.000; *** p<0.01 and ** P<0.05 Source: Authors' estimation from the SFA model.

In this study, the mean TE of considered major crops was 41% during the survey years in Southern Ethiopia. The average TE in 2011/12 was 39%, and it improved to 41% and 43% in 2013/14 and 2015/16, respectively. Similarly, on average TC, of aggregated major crops was 22.41% indicated a decline in TFP. The average TC in 2011/12 was 28.4%, and it declined to

21% and 18.3% in 2013/14 and 2015/16, respectively. Thus, uptake of technological practices in the production of crops through intensification has decreased in the study area. Consistently, the level of TFP decreased from 5.6 to 6.2 in 2011/12 to 2013/14 then, slightly declined to 5.9 in 2015/16 in the area study (Table 5.4).

Table 5.4.Summary of Mean TE, TC and TFP for major Crops in Southern Ethiopia

Efficiency parameters	Survey Year			
	2011	**2013**	**2015**	**Mean**
TE	0.39	0.41	0.43	0 .41
TC	0.28	0.21	0.18	0.22
TFP	5.89	6.45	6.19	6.19

Source: Authors' estimation.

3.4.Poverty Status of Households in Southern Ethiopia

The poverty line used for estimation was the PDC of Ethiopia by Diriba (2020). PDC estimated the poverty line using the cost-of-basic needs approach. Based on the 1995/96-2015/16 data, the annual poverty line for the year 2015/16 is determined to be Birr 7,184. A similar approach by the MoFED resulted in the same result (Diriba et al., 2020). Thus, households below the poverty line (the Head-Count Index) declined from nearly 19.28% in 2011/12 to 16.36% in 2013/14 then, 13.91% in 2015/16 (Table 5.5). It is consistent with the trend in the proportion of the poor people findings of Abro *et al.,* (2014).

Besides, the minimum requirement to bring all the poors to the level of the poverty line, the Poverty Gap Index, declined from nearly 7.12% in 2011/12 to nearly 6.29% in 2013/14 and 6.22% of the poverty line in 2015/16 (Table 5.5). While the Squared Poverty Gap Index declined between 2011/12–2013/14, its dramatic increment in 2015/16 means poverty worsened among the poorest households during this year. All indices of poverty in Table V indicated that many households moved into poverty in 2015/16. It is consistent with the findings of Dercon *et al.* (2011) in Southern Ethiopia.

Table 5.5.The FGT Poverty Indices for the Sample Households (in per cent) 2011-2016

FGT Poverty Indices	Survey Year			Mean
	2011	**2013**	**2015**	
Headcount ratio	0.19283747	0.16355811	0.13909224	0.165717
Poverty gap	0.07129104	0.06290473	0.06215935	0.065554
Squared poverty gap	0.0367768	0.03670821	0.04494887	0.039404

Source: Authors' estimation.

The choice of fixed effects over random effects is due to the Housman test results. We have an estimated model that uses the TE of households as an indicator of productivity. The coefficients of the explanatory variables in the model were statistically significant at a 5% and 1% level of significance. Besides, many of the coefficients of other variables used as control have the expected sign and individually significant at 10% or less significant. The findings indicated that TE has a positive and significant impact on increasing production and hence real household CEPC. On average, a 10% increase in TE increases household CEPC by nearly 7.3%. The land coverage and total income increase by 10 units, the real CEPC goes up by nearly by 0.3% and 0.4%, respectively (Table 5.6).

Table 5.6.Fixed Effects Regression Results: The Impact of Productivity on Real Household CEPC (in Birr)

Explanatory Variables	Coefficients	Std. Err.	t-test
Technical Efficiency	0.7325**	0.9730	0.75
Logarithm of area cultivated	0.0306*	0.0276	1.11
Logarithm of labor-force in man-days	-0.0051*	0.0036	-1.41
Logarithm of total income earned	0.0412***	0.0133	3.09
Dependency ratio	-0.0001*	0.00002	-1.64
Credit service used (yes =1)	0.0437*	0.0433	1.01
Prevention measures taken to prevent damage of crop by chemical (yes=1)	-0.0786***	0.0462	-1.70
Households' irrigation use (Yes = 1)	-0.0932** *	0.0367	-2.54
Households' participated in erosion prevention (yes=1)	0.1411***	0.0414	3.40
Households size	0.0746***	0.0176	4.24
Age of the head of the household	0.0101***	0.0038	2.71
Constant	8.1318***	0.3967	20.49
sigma_u	0.5879		
sigma_e	0.5218		
Rho	0.5593		
The overall Wald test statistic			
R-squared	0.1040		
corr(ai, Xb)	-0.1555		
F test that all u_i=0	2.52		

Note: (a)* significant at 10%, ** significant at 5%, *** significant at 1%. The dependent variable for all models is the logarithm of real consumption Expenditure per capita.

4. CONCLUSIONS

The more inefficient the households in the production process, then the poorer and the poorer in Southern Ethiopia during the survey years. However, there are variables in the regression model that affects real consumption per capita concomitantly. Results also suggested that combined efforts of TC and TE were needed to design policy interventions for increasing the productivity of the rural households.

Moreover, there was a negative impact on the productivity of considered major crops, indicating an inconsistency in family labour use, below 50% TE. Agriculture is vast yet, agriculture alone does not reduce poverty. However, further analysis is necessary to make more tangible claims about the poverty impact of productivity growth since we only focused on the direct effects of increasing considered crops farm productivity.

The percentage of households below the poverty line (Head Count Index) declined from nearly 19.28% in 2011/12 to 16.36% in 2013/14 and 13.91% in 2015/16. Besides, the level of minimum requirement of money relative to the poverty line declined from 7.12% in 2011/12 to 6.29% in 2013/14 and 6.22% in 2015/16. Though the sign of the coefficient of seed use is positive, its elasticity compared to the other explanatory variables was less responsive to the output. A 10% increase of land covered by considered crops, during the survey years is estimated to increase the aggregate production of major crops by 1.18%. The elasticity of ploughing oxen to the real value of output was also high.

Though average TE was increasing consistently throughout the survey years, the average TC of aggregated major crops was decreasing from year to year. In other words, households were less sensitive to the newly invented and other relevant production technologies in the area. The mean TFP of 6.19 for the considered major crops was exhibited a clear upward trend in the period of 2011/12-2013/14. Though an upward shift of TFP bent down from 2013/14-2015/16, it was positively affected by the overall growth of production during the survey years. Therefore, the policy implication is enhancing the TE; it is possible to improvement in the TFP and hence reduces poverty in the rural areas of SNNPR.

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CHAPTER SIX

SUMMARY, CONCLUSIONS AND POLICY IMPLICATIONS OF THE STUDY

6.1. Summary of the Study

This thesis analyzes the TFP at households' level and its impact on rural poverty in Southern Ethiopia using a strongly balanced panel dataset. In the second chapter of this thesis, in both exogenous and endogenous treatment cases, households who applied fertilizer achieved higher productivity than their counterpart. In endogenous treatment, the households have got much larger outputs than in the case of exogenous treatment. When the extension service participant increases by one unit in the exogenous and endogenous treatment cases, the farm household outputs of considered major crops enhanced significantly by 0.57 and 1.73 units, respectively.

Moreover, the positive effects of household heads' age were also slightly different in the exogenous and endogenous treatment cases 0.01 and 0.04, respectively, indicating that age matters the level of production in the study area. The male-headed fertilizer applying household also increases by one more percent the outputs of crops increases by 0.13% and 0.04% in both exogenous and endogenous treatment cases, respectively. A 10% increment in irrigated land access for households who applied fertilizer can affect the productivity considered crops differently in both exogenous and endogenous causes.

As agricultural inputs like land covered by the considered crops, oxen to cultivating; seed and labor force in man-days have a varied role across time. Households who used fertilizer during the survey years has got 109% surplus of considered major crops production than their counterpart. With the help of oxen to plow, seed, and labor force, households who used fertilizer can gain a much higher proportion surplus than their counterpart. Thus, households with irrigated land have also a significant proportion of difference among fertilizer applying households and their counterpart.

The second study estimated producer-specific TE of major crops produced in Southern Ethiopia. The result indicates that the time-varying inefficiencies parameter (η) was positive for the half-normal distribution, indicated that inefficiency has been declined over the survey years. The average estimated TE for crops in the study area ranges from 0.036 to 0.79 by a mean TE of 0.41.

The third chapter estimated TE by decomposing efficiency into farmer-specific latent heterogeneity, persistent, and transient efficiency. The models used in the analysis differed in their underlying. The models used decomposed technical inefficiencies into time-variant/invariant, and farm-heterogeneity effects. The TFE-model disentangled time-varying inefficiencies from time-invariant heterogeneity. The KLH and KH models distinguished between persistent and transient inefficiencies and the FE-model for estimating time-invariant efficiencies for comparison purposes. Consequently, models used for the analysis have shown very different estimates of overall efficiency levels in reducing downward and upward biases in the study area.

Generally, the estimated TE implied that improvement in efficiency, Southern Ethiopia can capture about 39% to 99% of the un-captured or untapped maximum considered crop production. The mean efficiency increased from 63.82% to 72.72% in 2011/12 to 2013/14 and then declined to 56.62% in 2015/16 in the study area. Averagely, there is a positive return to scale yet decreased from 87.05% (2011/12) to 77.53% (2013/14) and then declined more to 62.8% (2015/16). The average TC in 2011/12 was 20.67% and declined much more to 9.44% and 5.82% in 2013/14 and 2015/16, respectively. Here is to mean, households were less sensitive to the newly invented and other relevant production technologies during the survey years.

Thus, uptake of technological practices in the production of crops through intensification has decreased in the study area. Consistently, the level of productivity was reduced from 5.62 to 6.18 in 2011/12 to 2013/14 and then declined more to 5.94 in 2015/16. The percentage of households below the poverty line (Head Count Index) declined from nearly 19.28% in 2011/12 to 16.36% in 2013/14 and 13.91% in 2015/16. Besides, the minimum requirement of money relative to the poverty line is required to bring all the poor to the level of the poverty line. The Poverty Gap Index declined from nearly 7.12% in 2011/12 to 6.29% in 2013/14 and 6.22% of the poverty line in 2015/16. Although the sign of the coefficient of improved seed use was positive, its elasticity compared to the other explanatory variables becomes less responsive to the output. A ten percent increase in land coverage by those crops during the survey years is estimated to increase the aggregate production of major crops by about 1.18%. The elasticity of plowing oxen to the real value of production is also high in the area.

Though average TE increased consistently throughout the survey years, the average TC of aggregated major crops decreased from year to year. That means households are less sensitive to the newly invented and other production technologies in the area. The mean TFP of 6.19 for the considered major crops exhibited a clear upward trend in 2011/12-2013/14. Though an upward shift of TFP bent down from 2013/14-2015/16, its growth was positively affected by the overall output during the survey year.

6.2. Conclusion

The cultivated area of land, use of fertilizer, participating in the extension system, and accessing irrigation water are the determinants of productivity growth of those considered crops in the study area. It was observed that the technical inefficiency effects were significant and, its effect is found to gradually increasing over time. This study mainly indicated that farmers can increase their output level of considered crops with the same level of inputs by simply improving the status of efficiency and technology adoption. The TE value indicated that most households are not technically efficient in producing crops in the study area.

The conclusion is that TC and TE become the determinant drivers of TFP growth of crops considered in the study area. Sorghum has lesser TFP than any other major crops in the study area, indicating households have been using a lesser amount of inputs for its production. Therefore, it is possible to argue that farmers could decrease inputs (labor force, oxen for plowing, land, fertilizer, and seed) averagely by 22 percent to the existing amount of output.

However, maize and teff have got top ranking TFP and nearly the same productivity level. Comparatively, the productivity of wheat and maize crop was positively and significantly affected by the higher participation level of households in the extension system, indicating that those households who participate in the extension system were able to relatively more productive than the others. The significance level of efficiency and sensitivity for technology in the production process of considered crops is briefly indicated in the study area. Focusing on the prominent drivers of productivity such as input use, the technology adoption practices, and engagement in extension packages increased TFP in the study area.

The results also show differences in inefficiency at the zonal level during the survey years. The results confirmed that the farmers were unable to achieve a higher proportion of production. The wide variations in estimates of efficiencies indicated that most of the producers were inefficient. Therefore, there is ample room for improving crop production by improving the existing levels of efficiency. Therefore, in terms of the ranking of the zonal averages, Derashe emerged as the best performer followed by Burji Special, Gurage, Sidama, and Woliata, indicated that the total production and productivity within these zones improved significantly during the survey years. The analysis of households' performance across Zones and their position compared within zones with better efficiency scores could indicate the status of each Zone in the study area.

Moreover, there was a negative impact on the productivity of the considered major crops, indicating the inconsistency of family labor use. Agriculture is significant, yet agriculture alone does not reduce poverty. However, further analysis is necessary to make more tangible claims about the impact of productivity growth in poverty since we only focused on the direct effects of increasing considered crop farm productivity.

6.3. Policy Implication

This study identified every agricultural input used in the production of those considered crops has a pivotal role in influencing the productivity of the crops. Among the others, fertilizer application has a vast impact on the productivity of considered crops. Crop rotation has a relatively higher impact on barley and wheat crops than other considered crops. Enhancing the use of improved techniques of production should take part in the development policy of the area. Training on production technologies, supply of sufficient improved seed and fertilizer, reducing crop loss, land conservation, and best experience sharing should get the policy focus in the area.

Moreover, creating a platform for regular communication of extension workers with farmers to have valuable insights and sharing experiences to empower the design of policy for extension approaches. Policies should have a strong orientation on ways of mitigating those persistent inefficiencies in the study area. The fourth chapter indicates the poorer households were inefficient and less productive during the survey years. The econometric results also show that increasing TE is critical in improving the welfare of households in the area.

Agricultural policies that are tailored to enhance production efficiency and technological adaptability across the region should dominantly be converged for the productivity of the considered crop. Moreover, policy including poverty reduction strategies focusing on those considered crops that can tackle poverty incidences has to symbolize in the area.

APPENDIX 1

RESEARCH INTERVIEW AND FOCUS GROUP DISCUSSION CHECKLISTS

Introduction

The researcher, Merihun Fikru is one of the Ph.D. candidates in Rural Development Studies at the College of Development Studies in Addis Ababa University. He is currently researching the partial fulfillment of a Ph.D. His study is entitled, **"Agriculture Input Use, Total Factor Productivity Growth, and Rural Poverty: Dynamics and Patterns in Southern Ethiopia."** The main purpose of this interview and FDG is to collect qualitative data on the study's topic. The response that you are going to give for all the questions will anonymously be included in the analysis of the study, and the findings of the study will be used only for academic purposes. Hence, feel free while responding to the questions as your genuine response will subsequently determine the overall quality and reliability of the study.

INTERVIEW CHECKLIST FOR KEY INFORMANTS

1. Do farmers regard the improved varieties of crops as profitable, given the additional investment of time and resources?
2. What are the major crops grown in your area and which one do you prefer more? For how long you produced?
3. Are interested farmers able to procure the required inputs such as seeds, fertilizers, insecticides, pesticides, tractors, and other machinery in time?
4. Is there a supply problem for chemical fertilizer, improved seeds, and chemicals for protection for the major crops?
5. How is a natural hazard in your area? What factors do think can affect the productivity of teff, maize, barley, wheat, and sorghum in your area? Which one is more susceptible to damage? Is there any timely changing factor that reduces the outputs of major crops?
6. Do they face problems in securing short-term credit from the government and other microfinance to purchase the required inputs?
7. Is the productivity of the improved variety able to supply products for the market and fulfill the food and nutrition demand of the households?
8. Do farmers believe that they are likely to get timely technical advice about the package from the agricultural extension service when needed?

9. What are the socioeconomic characteristics of farmers who are using various technologies and adopting new inputs?
10. What proportion of farmers abandoned the new technologies during extension time?
11. What proportion of targeted farmers is using the new technologies?
12. Are there any factors that can limit the technology adoption or TELC by the local farmers in your neighborhood?
13. How is the extension delivery system in your area? Do people get all inputs basically, the main crops seeds on time? On what modality?
14. Do you think that family labor can contribute more to the efficiency of farm work?

FOCUS GROUP DISCUSSIONS

Introduction by Moderator/ Assistant Moderator

WELCOME!

Thanks for agreeing to be part of this focus group discussion. We appreciate your willingness to participate.

PURPOSE OF FOCUS GROUPS

This group is expected to conduct the focus groups on the checklist given below. The reason that the researcher is having these focus groups discussion, to find out the impact of agricultural input use on the growth and efficiency of crop production in Southern Ethiopia. We need your input and want you to share your honest and open thoughts with us.

GROUND RULES

- We want you to do the talking.

We would like everyone to participate. I may call on you if I haven't heard from you in a while.

- There are no rights or wrong answers

Every person's experiences and opinions are important. Speak up whether you agree or disagree.

- We want to hear a wide range of opinions.

What is said in this room stays here?

We want folks to feel comfortable sharing when sensitive issues come up.

- We will be tape recording the group

We want to capture everything you have to say. We don't identify anyone by name in our report. You will remain anonymous.

Checklists/Questions

1. For how long and how have you been involved in the agricultural sector?
2. Think back over ten years that you have participated and tell us your highest productivity or highest production achievement year, seasons, crop type.
3. Think back over ten years that you have participated in agriculture and, tell us the technologies and inputs that you adopted and not adopted, then for not adopted technologies and inputs specify your reasons why you didn't.
4. What needs improvement?
5. Over the last ten years, how do you see the poverty within your household and your friend's households?
6. Have you ever changed the technologies accessed for your agriculture and do you believe that improving the best agronomic management system can enhance the productivity of your agriculture?
7. How do you evaluate the poverty level within your community?
8. Is there a gender issue? Which farmers, male or female, are expected to do extra work?

What can each one of us do to make agriculture better?

Addis Ababa University
College of Development Studies
Office of the Associate Dean for Research and Technology Transfer
Template for Reporting Plagiarism Assessment

Name of the Center Rural Development Studies Program of study: Regular Program level(Masters/PhD):PhD Please, check one: **Regular**/Continuing

Name of the Adviser/s : Associate Prof. Bamlaku Alamirewu Alemu (PhD) and Associate Prof. Maru Shete (Ph.D.)

Topic of the dissertation/thesis: **Agriculture Input Use, Total Factor Productivity Growth and Rural Poverty: Dynamics and Patterns in Southern Ethiopia**

Table Showing Matched and Changed Text

No.	Matched Text	Changed Text	Page number
1	Presented in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Rural Development Studies Addis Ababa University, Addis Ababa, Ethiopia, May 2021 Addis Ababa University College of Development Studies, Center for Rural Development Studies.	It is standard format	Cover page
	DECLARATION:This is to certify that theP.h.D. dissertation research prepared by MERIHUN FIKRU which is titled: “Agriculture Input Use, Total Factor Productivity Growth and Rural Poverty: Dynamics and Patterns in Southern Signed by the examining Committee: External examiner: -----------------------Signature: --------------------- Date:--------------------- Internal examiner:------------------------------Signature:---------------------Date:---------------- Main (chair) Supervisor: --------------------------Signature: ------------------Date: ---------------- Co-supervisor----------------------------------Signature: ---------------------Date:-------------------	It is standard format	ii
2	First and foremost, I owe it all to Almighty God 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 Ph.D. study. They all deserve my sincere appreciation. I am grateful to all of you in one way or another played a part in the successful completion of this thesis. Above all, I am very grateful to my main Supervisor Associate Professor Bamlaku Alamirewu (Ph.D.), for his relentless, sympathetic, and continuous support during my doctoral research journey. His scientific guidance and encouragement from the beginning to the completion of the course and thesis are commendable. His critical comments, though at times very stringent, 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.	Commonly used terms for acknowledgment	iv
3	LIST OF TABLES x LIST OF FIGURES xii LIST OF ACRONYMS AND ABBREVIATIONS xiii CHAPTER ONE 1 1. INTRODUCTION 1 1.1. Background of the Study 1 1.2. Statement of the Problem 2 1.3. Objectives of this Dissertation 4 1.3.1. General Objective 4 1.3.2. Specific Objectives of the	Standard format	viii

	Study were 4 1.4. Philosophical Orientation of the Study 5 1.5.		
4	FIGURE 4.1. DISTRIBUTION OF PERSISTENT EFFICIENCIES ACROSS MODELS 81 FIGURE 4.2. DISTRIBUTION OF TRANSIENT EFFICIENCIES ACROSS MODELS 81	Standard format	xi
5	Out of the total grain crop area, 81.27% was under cereals: teff 1 , maize, sorghum and wheat took up 24.00%, 16.98%, 14.97%, and 13.49% of the grain crop area, respectively. Cereals contributed 87.42% of the grain production. Maize, teff, wheat and sorghum	The land covered by teff[1](24%), maize(16.98%), sorghum (14.97%), and wheat (13.49%) of the total grain cultivation, 87% was produced by these crops in Ethiopia (McGuire, 2015; Abafita et al., 2016; Sandhu, 2019).	2
6	policy-relevant technology shifters by examining their effects on inefficiency components.	It also identifies policy points that can shift the status of inefficiency components.	3
7	to the best of the researcher's understanding, this is the first research using strongly balanced short panel data addressing the problems of household and farm heterogeneities in measuring efficiencies in Southern Ethiopia's	Finally, according to the researcher's understanding, it could be the first research, addressing the problems of household and farm heterogeneities by using strongly balanced short panel data in Southern Ethiopia considering major crops produced in the area.	4
8	Schmidt and Sickles (1984). Agasisti et al., 2017 assumes inefficiency effects to be time-invariant and individual specific and Heshmati, 2020 Estimates of persistent and transient inefficiencies without accounting for farm heterogeneity. split the error term into three components where εit captures a random shock; ωi captures individual effects as persistent inefficiency; and φit captures the transient inefficiency component. provides estimates of persistent and transient inefficiencies separating them from time-invariant farm effects and noise.	Mathematical equations and authors' names	7
9	-dissertation is organized into five chapters. The first chapter is the introductory chapter provides a summary of the -statement of the problem, objectives of the dissertation, and methodological approaches including the datasets used in the	This thesis is organized in five chapters. The first chapter is the introductory chapter narrates summarized thesis	8
10	statement of the problem, objectives of the dissertation, and methodological approaches including the datasets used in the	Standard used in a dissertation	9
11	productivity growth, and poverty reduction in rural Ethiopia. World development 59 (2014): 461-474. no. 6 (2015): 798-814. Asefa, Shumet. Analysis of Efficiency of crop producing smallholder-farmers in Tigray, Ethiopia.(2011): 1-25. Bachewe, Fantu. The state of subsistence agriculture in Ethiopia: sources of output growth and agricultural inefficiency. (2009). Farm-heterogeneity, persistent and transient productive efficiencies in Ethiopia's smallholder cereal farming. 2020, Shiferaw, and Jacob Ricker-Gilbert. Impact of improved maize adoption on welfare of farm-households in Malawi. J. Spielman, Dawit Alemu, and Madhur Gautam. Policies to promote cerealintensification in Ethiopia: A review of Savastano, and Alberto Zezza. Fact or artifact: The impact of measurement errors on the farm size–productivity relationship. Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. Journal of Agri. Science 6, no. 10 (2014): 108. Kumbhakar, Gianmaria M., and Giorgio Vittadini. Closed-skew normality in stochastic frontiers with individual effects and	References	11-16

	long/short-run efficiency. Journal of Prod. Analysis 42, of African economies 14, no. 4 (2005): 559. Dercon, Stefan, and Luc Christiaensen. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. Kremer, and Jonathan Robinson. How high are rates of return to fertilizer? Evidence from field experiments in Greene, Willam. Fixed and random effects in stochastic frontier models. Journal of productivity analysis 23, Sen. Productivity measurement in Indian manufacturing: A comparison of alternative methods. Analysis of technical efficiency of small holder maize growing farmers of Horo Guduru Wollega Zone, Ethiopia: A stochastic frontier approach. Spielman, D.J., D. Byerlee, D. Alemu, and D. Kelemework. Policies to promote cereal intensification in Ethiopia: The search for appropriate public and private roles. Food Policy 2010, 35, 185–194. O'Donnell, Christopher J.Nonparametric estimates of the components of productivity and profitability change in and Gezahegn Ayele. Can modern input use be promoted without subsidies? An analysis of fertilizer in Ethiopia. Agricultural Economics 44,		
12	farm level and aggregate adoption. At the individual level, adoption is defined as the level of using technology in	In the first case, adoption depends on the use of technology in the long-run equilibrium	18
13	aggregate adoption is measured by the aggregate level of technologies invented within a given geographical area,	Therefore, diffusion implies agricultural input adoption is measured within a given geographical area	18
14	Ethiopia's: agriculture and food economy, accounting for about three-fourths of the total area	Ethiopia's economy is dominated by agriculture for food production	20
15	Umesh, A. Pouyan Nejadhashemi, and Sean A. Woznicki. Climate change and eastern Africa: a review of the impact on major crops. Bachewe, Fantu. The state of subsistence agriculture in Ethiopia: sources of output-growth and agricultural inefficiency. (2009). Dereje, and Alemayehu Seyoum Taffesse. Land constraints and agricultural-intensification in Ethiopia: A village-level analysis of high-potential areas. Petrin. Estimating production functions using inputs to control for unobservables. The review of economic studies 70, Tigist. Productivity and household welfare impact of technology adoption: Micro-level evidence from rural Ethiopia. UNU-MERIT Working Paper Tefera, Nicholas Minot, and Gezahegn Ayele. Can modern input use be promoted without subsidies? An analysis of fertilizer in Ethiopia. Spielman, David J., Dawit Kelemwork, and Dawit Alemu. Seed, fertilizer, and agricultural extension in Ethiopia. Food and agriculture in Ethiopia: Progress and policy Solomon Bizuayehu. Technical efficiency of major crops in Ethiopia: Stochastic frontier model, 2014.	References	39-42
16	Out of the aggregate grain crop area, 81.27% was under cereals: teff, maize, sorghum and wheat took up 24.00%, 16.98%, 14.97%, and 13.49% of the grain crop area, respectively. The cereals shared 87.42% of the total grain	The land covered by teff[1](24%), maize(16.98%), sorghum (14.97%), and wheat (13.49%) of the total grain cultivation, 87% was produced by these crops in Ethiopia (McGuire, 2015; Abafita et al., 2016; Sandhu, 2019).	44

	production.Sorghum, maize, teff, and wheat shared 27.02%, 17.29%, 15.63%, and 16.36% of the production,		
17	which is assumed to be independently and identically distributed as	assuming its distribution as half-normal distribution above	48
18	are respectively, the idiosyncratic and inefficiency components of the "composed error term",	are the idiosyncratic and inefficiency components of the composed error term in the same	48
19	has approximately a chi-square distribution ($\chi2$), distribution with q equal to the number of parameters assumed to be zero in the	Mathematical equation	52
20	of fertilizer used in Kg 0.0487*** 0.01 10.38 0.000 Logarithm of seed used in Kg 0.0334*** 0.01 6.17 0.000 Logarithm of labor force in man-days 0.0336*** 0.01 5.77 0.000 / of fertilizer used in Kg 0.0411*** 0.04 0.01 8.11 Logarithm of seed used in Kg 0.0335*** 0.03 0.01 5.40 Logarithm of labor force in man days 0.0374** 0.04 0.01 5.72 / Moreover, the model predicted that the mean level of TE for crops is 41.22%. given the level of input and the existing technology, there is room to boost	Empirical work obtained	53
21	Alemu, and Munir A. Hanjra. Policies for agricultural productivity growth and poverty-reduction in rural Ethiopia. World development59 (2014): 461-474. Ayele, G.; Bekele, M.; Zekeria, S. Productivity and Efficiency of Agricultural Extension Package in Ethiopia, The Ethiopian Development Research Institute Res: Addis Ababa, Ethiopia, 2006, Bachewe. F.N. The State of Subsistence Agriculture in Ethiopia: Sources of Output Growth and Agricultural Inefficiency. Ph.D. dissertation, University of Minnesota, USA, 2009, D.S.; O'Donnell, C.J.; Battese, G.E. An Introduction to Efficiency and Productivity Analysis; Elsevier: New York, 2005, pp 69–97. Coelli T. Colombi, R.; Kumbhakar, S.C.; Martini, G.; Vittadini, Closed-skew Normality in Stochastic Frontiers with Individual Effects and Long/Short-run Efficiency. Kumbhakar, S.C.; Wang, H.; Horncastle, A.P. A Practitioner's Guide to Stochastic Frontier Analysis Using Stata. Cambridge University Press: Cambridge, UK, 2014, pp. 1–357. Kumbhakar, S. Lai H.P. Panel-Data Stochastic Frontier Model with Determinants of Persistent and Transient Inefficiency. Petrin. Estimating production functions using inputs to control for unobservables. The Technical Efficiency of Farming Systems Across Agro-ecological Zones in Ethiopia. O'Donnell, C.J. Non-Parametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture. Shumet, A. Analysis of Technical Efficiency of Crop Producing Smallholder Farmers in Tigray Ethiopia; Mekelle University, 2011, pp 1–25, Available online: https://mpra.ub.uni-muenchen. Taffesse, A.S.; Dorosh, P.; Asrat, S. Crop Production in Ethiopia: Regional Patterns and Trends. Development strategy and governance division; International Food Policy Research Institute IFPRI: Wasse Technical Efficiency of Major Crops in Ethiopia: Stochastic Frontier Model. Acad. J. Agric. Res. 2014, 2, 147–	References	59-63

	153. panel data models to distinguish between time-invariant farm-heterogeneity, persistence, and		
22	components of inefficiency and their separation from unobserved heterogeneity effects	Evaluation of long-run and short-run inefficiency separation of unobserved heterogeneity effects have the reverse orientation on promoting efficiency	65
23	Teff 5 (Eragrostis), wheat (Triticum), maize (Zea Mays), barley (Hordeum Vulgare),	Scientific names of the crops	66
24	in separating the inefficiency effects as an explicit function of the vector of firm/farm-specific variables plus random error	helps to appropriately separate the inefficiency effects as an explicit function of individual-specific variables plus random error which can overcome the problems of inconsistencies.	67
25	this model allows inefficiency parameters and TE to vary across time in a potentially different	Thus, it allows inefficiency parameters vary across time in different manner and approves a high predictability across farms.	67
26	et al., (2018) acknowledged four alternative SPF panel data models for estimating and analyzing long-run and short-run efficiencies disentangling them from time-invariant farm effects. The first model is the	However, As Heshmati *et al.,* (2018) acknowledged four alternative SPF panel data models for estimating long-run and short-run efficiencies dis-aggregating them from time-invariant farm effects. The untouched are Standard model name and expression.	
27	assumes inefficiency effects to be time-invariant and individual-specific that can offer estimates of long-run inefficiencies. The second model is	The FE which assumes inefficiency effects to be time-invariant and individual-specific that can offer estimates of long-run inefficiencies, was considered as the first model. The next model…	68
28	treated as long-run inefficiencies To specify a model with time-invariant inefficiency effect, we treat a time-invariant term to represent long-run inefficiency to	Model 1: Fixed-Effect Model treated as long-run inefficiencies…. Sub-title and the others are standard formula name	68
29	obtain: yit=σ0+fXit;θ +εit -ui (1) This model utilizes the panel feature of the data via, plus it can be estimated when the inefficiency component ui is a fixed parameter by the FE-model.	Mathematical equation	69
30	this model has been criticized for its assumption about inefficiency,	However, there are critics on the model assumption about inefficiency,	69
31	random-effects to capture any long-run farm-heterogeneity, not inefficiency αit represents transient inefficiency and Vit is a random shock with the following distribution:	random-effects to capture any long-run farm-heterogeneity, not inefficiency αit represents transient inefficiency and Vit is a random shock with the following distribution:	69
32	as a fixed-parameter that cannot capture inefficiency, the model is considered as a TFE-model. The TFE-model allows inefficiency to be time-variant and controls for farm-heterogeneity to capture by a farm-specific intercept and assumes that inefficiency terms are always transient. Thus, it fails to capture persistent	Standard definition given for mathematical equation.	69
33	Model 3: Individual effects treated as persistent inefficiencies To overcome the downward bias	This is the way how the objective should be analyzed	70
34	inefficiency estimation of the TFE-model and its ignorance about the steadfast inefficiency component, Kumbhakar and Heshmati (1995) proposed a model that treats individual effects as	The name of a model and authors	70
35	model (KH-model) split the error term into three components where εit captures a random shock; ωi captures individual-effects as steadfast inefficiency; φit captures the transient inefficiency component (	The name of the model	69 and 70
36	ignoring the difference between the true and predicted values of	and leaving the variation among the true and predicted values	70
37	Teff (Eragrostis), wheat (Triticum), maize (Zea Mays), barley (Hordeum Vulgare)	Scientific name of the crops	71
38	Alternatively, this is to test whether the SPF function is more appropriate than the conventional	SPF function is the name standard production model	73

39	no unobserved heterogeneity, no observed heterogeneity, and the assumption of constant inefficiency over term for technical inefficiency are rejected at the 1% level of significance. Therefore, unconstrained TE, a time-varying,	Technical terminologies	74
40	varying, and half-normal distribution for inefficiency were estimated (Table 4.4). Table 4.4. PROPERTIES OF WALD TEST STATISTIC Hypotheses LL H0 LL H1 Wald Test Statistic p-Value No unobserved heterogeneity H0: Var (uit)=0 H1 :Var (uit)≠0 578.55 0.000 No observed heterogeneity H0:	Technical terminologies	74
41	The robustness checks showed how regression coefficient estimates behaved when the regression specification changed in some way, usually by adding or removing	By adding or removing explanatory variables, the robustness checks were performed.	74
42	has approximately a chi-square distribution ($\chi 2$), distribution with q equal to the number of parameters assumed to be zero in the	chi-square is technical terminology	
43	estimations across models and that the efficiency scores are sensitive to the model's specifications (	Thus, the other model's results illustrated significant variations from KLH-model are sensitive to the model's specifications	75
44	to get a better picture of efficiency components in different models, we used density plots for	Furthermore, by using density plot, it was possible to find efficiency components in different models.	79
45	kernel = epanechnikov, bandwidth = 0.0703Kernel density estimate image9.emf 0 2 4 6 Density 0 .2 .4 .6 .8 1 KH_TE kernel = epanechnikov, bandwidth = 0.0496Kernel density estimate .6 .62 .64 .66 .68 .7 Density 0 .2 .4 .6 .8 Technical efficiencyKLH_TE kernel = epanechnikov, bandwidth = 0.4657 Kernel density estimate FIGURE 4.1.	Standard formula given	80
46	Density 0 .2 .4 .6 .8 1 Technical efficiency via exp(-E(u|e)) kernel = epanechnikov, bandwidth = 0.6375Kernel density estimate image11.emf .38 .4 .42 .44 .46 .48 Density 0 .2 .4 .6 .8 1 Technical efficiency via exp(-E(u|e)) kernel = epanechnikov, bandwidth = 0.6514Kernel density M. A. Policies for agricultural productivity growth and poverty reduction in rural Ethiopia., 2014,	Standard formula given	80
47	M. A. Policies for agricultural productivity growth and poverty reduction in rural Ethiopia., 2014, Bachewe, F. N., Berhane, G., Minten, B., & Taffesse, A. S. Agricultural growth in Ethiopia (2004-2014): Evidence and drivers (Farm-heterogeneity and persistent and transient productive efficiencies in Ethiopia's smallholder cereal farming., 2020, Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia, 2014, Journal of Agricultural Science, 6(10),108. Colombi R, Kumbhakar SC, Martini G, Vittadini G. Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency, 2014, J Prod Anal. 42 (2):123-136. Colombi, R., Martini, G., and Vittadini, G. Greene, W. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. 2005, JE,126(2), 269- 303. Greene WH. Fixed and random effects in stochastic frontier models, 2005 Heshmati, A., Kumbhakar, S. C., and Kim, J. Persistent and transient efficiency of international airlines, 2018, European Journal of Transport and Infrastructure Research,18(2).	references	83-85

	Sen, K. Productivity measurement in Indian manufacturing: A comparison of alternative methods, 2011, A. Efficiency measurement in Swedish dairy farms: An application of rotating panel data 1976-88., 1995, Kumbhakar, S. C., Wang, H., and Horncastle, A. P. A practitioner's guide to stochastic frontier analysis using Stata, 2015, A. Cambridge University Press. Lai, H. P., and Kumbhakar, S. C. Panel data stochastic frontier model with determinants of persistent and transient A. inefficiency, 2018, B. Petrin. Estimating production functions using inputs to control for unobservables. The review of economic studies 70, journal of agricultural research, 17(1), 6. Taffesse, A. S., Dorosh, P., and Gemessa, S. A. Crop production in Ethiopia: A. Regional patterns and trends. Food and agriculture in Ethiopia: Progress and policy challenges, 2012, 53-83. B. Technical efficiency of smallholder agriculture in developing countries: the case of Ethiopia, 2020, C. Technical efficiency of major crops in Ethiopia: stochastic frontier model, 2014, Acad. J. Agric. Res. 2(6):147-153.		
	total area cultivated, 89% of the grain crops produced in the Meher cropping season in 2015 (Hvits and, C. (2016). The aforementioned implies that productivity growth directly affects the welfare of	Deleted	87
	which is assumed to be independently and identically distributed as	term, assumes the distribution as half-normal distribution above	91
	are respectively, the idiosyncratic and inefficiency components of the "composed error term",	are the idiosyncratic and inefficiency components of the composed error term in the same order	91
	has approximately a chi-square distribution ($\chi 2$), distribution with q equal to the number of parameters assumed to be zero in the	Standard formula	
48	the minimum amount of money relative to the poverty line required to bring all the poor to the level of the poverty line, the	Besides, the minimum requirement to bring all the poor to the level of the poverty line, the	97
	the minimum amount of money relative to the poverty line	the level of minimum requirement of money relative to the poverty line declined	100
49	M. A. Policies for agricultural productivity growth and poverty reduction in rural Ethiopia.2014, Addai, K. N., and Owusu, V. Technical efficiency of maize farmers across various agro-ecological zones of Ghana.2014, Journal of Agriculture and Environmental Sciences, 3(1), 149-172. Alene, A. D. Productivity Growth and the Effects of R&D in African Agriculture.2010, Agricultural Economics 41: Bachewe, F. The state of subsistence agriculture in Ethiopia: sources of output growth and agricultural inefficiency.2009 Bigsten, A., and Shimeles, A. Poverty transition and persistence in Ethiopia: 1994–2004. 2008, World Development, 36(9), 1559-1584. Brink, A. Carletto, C., S. Savastano, and A. Zezza. Fact or artefact: The impact of measurement errors on the farm size–productivity relationship. 2013, S. C., Martini, G. and Vittadini, G. Closed-Skew Normality in Stochastic Frontiers with Individual Effects and Long/Short-	References	101-103

	Run Efficiency.2014, Journal of Productivity Analysis, 42(2), 123–136. Demeke, A. B., Keil, A., and Zeller, M. Using panel data to estimate the effect of rainfall shocks on smallholders' food security and vulnerability in rural Ethiopia.2011, Climatic change, 108(1), 185-206. Dercon, S., and M. M. Crop-Livestock inter-linkages and climate change implications for Ethiopia's agriculture: A Ricardian approach. Kumbhakar, S. C., Wang, H., and Horncastle, A. P. A practitioner's guide to stochastic frontier analysis using Stata.2015, Cambridge University Press. Lai, H. P., and Kumbhakar, S. C. Panel-data stochastic frontier model with determinants of persistent and transient inefficiency. 2018, Spielman, D. J., Byerlee, D., Alemu, D., and Kelemework, D.Policies to promote cereal intensification in Ethiopia: A review of evidence and experience.2010, Food Policy, 35(3), 185-194. Taffesse, A. S., Dorosh, P., and Gemessa, S. A. Crop production in Ethiopia: Regional patterns and trends. Food and agriculture in Ethiopia: Progress and policy challenges.2012, 53-83. Total factor productivity estimation: A practical review." Journal of economic surveys 26,		
49	the analysis 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. The TFE-model disentangled timevarying inefficiencies from time-invariant heterogeneity. The KLH and KH models distinguished between persistent and transient inefficiencies and the FE-model for estimating time-invariant efficiencies for comparison purposes.	The models used decomposed technical inefficiencies into time-variant/invariant, and farm-heterogeneity effects.	105
50	the minimum amount of money relative to the poverty line	the minimum requirement of money relative to the poverty line to bring the poor	105
51	production efficiency. The wide variations in estimates of efficiencies across farmers and over time indicated that most of the farmers were still using their resources inefficiently in the production process and, there still have ample room for improving crop production by improving the existing levels of efficiency.	proportion of production. The wide variations in estimates of efficiencies indicated that most of the producers were inefficient. Therefore, there is ample room for improving crop production by improving the existing levels of efficiency.	107