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TECHNOLOGIES AND LAND PRODUCTIVITY: EVIDENCE FROM RURAL ETHIOPIA

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Technologies and Land Productivity: Evidence from Rural Ethiopia

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Abstract

This study aims to examine the impact of agricultural technologies on land productivity in rural Ethiopia by applying three econometric models namely: fixed effects (FE), quantile regression, and probit regression model were using the Ethiopian socio-economic survey of 2011/12, 2013/14 and 2015/16 data, collected by Central statistical Agency (CSA) in collaboration with the World Bank. The panel fixed effect result shows that improved technologies have a positive impact on land productivity except for pesticides. The author also estimates quantile regression to see whether the same set of variables determine land productivity. The result indicates that technologies such as fertilizer, improved seed, and fungicide were positive and significant in determining land productivity. This implies that the adaption of these technologies improves land productivity at least in the study area. So it is recommended to adopt these technologies to increase land productivity. The policy package might also include crop rotation, health reform, education, and labor intensification. This study also measures vulnerability as the probability that a household's level of production falls below the appropriate production level in the future. The probit model estimation result shows that vulnerability is higher among the low productive and exhibited an inverse correlation with the adaption of technologies. The important policy implication of this is that the current agricultural extension program and safety net program could focus on the promotion of and support for the adaption of these improved technologies to rescue rural farmers from vulnerability. There is a discrepancy between lower productive and higher productive in terms of vulnerability when they adopt a given technology. Therefore, policymakers should take into account this heterogeneity to unleash the maximum possible benefit of the technology practices.

Keywords: Land Productivity, Rural Ethiopia, Technologies, Vulnerability

Declaration

I, Zewditu Mequanint, declare that this thesis entitled with, "Technologies and Land Productivity: Evidence from Rural Ethiopia" is my own work for the partial fulfillment of the requirements for the degree of Master of Science in Economics (Natural Resource and Environmental Economics) at Addis Ababa University, has been approved and confirmed by the following committee:

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Advisor ——————————————Signature—————Date—————-

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Chairperson of Graduate Program

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Chapter 1

Introduction

1.1 Background of the Study

Productivity can be expressed as "*the ratio of production output to the ratio of inputs which measures how efficiently production inputs, such as land, labor, and capital are being used in an economy to produce a given level of output for the key for economic growth and competences*" (OECD, 2001 a). In this respect, land productivity can be seen as an increase in yield level from the given plot area, and an agricultural technology practice is the application of scientific wisdom to the practical aim of farmer's life improvement and is novel to its users (Kosmowski et al, 2020 b). Hence, technologies in the agricultural sector have enhanced land productivity in a way of increasing the current fertility of the land and make the farmers in having adequate livelihood income or surpassing some social basic required needs (OECD, 2001 b).

Having this, understanding the nature and effect of technologies, its advantage, and disadvantage, and in particular, the chance of advancing productivity is a key to derive appropriate policies targeted to increase it (Wiredu et al, 2010). Many studies analyzes adoption of new technologies and productivity from a static point of view but it needs to be investigated from a dynamic point of view if productivity analysis has to aid policymaking and evaluate the effect of certain shock on yield level. According to Pilo (2019), Wiredu et al (2010), and Alene (2010) investigating land productivity dynamics is necessary for serving at least the following three targets: estimating the risk of technologies and the probability of increasing productivity; identifying the reasons associated, respectively, with land productivity shock, and identifying the best practice from different types of technologies; and examining the social mobility prospects of individuals in different land fertility. In particular, distinguishing households that have not applied innovations occasionally from those that are applying all the time is of practical importance, because the types of intervention relevant for dealing with productivity are likely to be different in both cases.

Generally speaking, productivity is an outcome of innovation in one way or another. To analyze appropriate forward-looking land productivity interventions, however, it may be preferable to assess the future possibilities that a household will be vulnerable to yield shock. Vulnerability is defined as the risk a household will fall into a yield shock in the future (Temesgen et al, 2009). Hence, vulnerability is an important aspect of households' experience of yield shock which puts them in the hardship of poverty. Many households that are not currently in loss of productivity recognize that they are vulnerable to events of bad harvest or an economic downturn that could easily push them into loss of productivity in the future (Naude et al, 2009). The measurement of vulnerability due to the adoption of technologies is particularly important for monitoring the future loss of productivity for the farmer's communities and also for the design of risk reduction policies (Twigg, 2004).

Although Ethiopia has recorded robust economic progress in recent years, low productivity is still pervasive in rural Ethiopia (i.e. the agricultural sector contributes lower compared to the service sector) (World Bank, 2020). More importantly, the low yield level in agricultural products in Ethiopia is still a predominantly rural phenomenon (MoFED, 2008). Thus, this study aims to examine the impact of adation and application of new emerging technologies on land productivity in rural Ethiopia.

1.2 Statement of the Problem

Africa requires raising land productivity in agriculture. The systematic use of modern inputs like fertilizer, improved seed, pesticides, and hybrid seed is a pathway to increase productivity, but adoption of these technologies remains low (Bold et al, 2017). Although Bold et al. (2017) argued like this, the adoption of such modern technologies may have a devastating impact on land productivity in years to come. Thus, studies are needed in investigating ways to substantially increase current as well as future land productivity in line with basic agricultural technologies available to smallholder farmers.

In Ethiopian agricultural literature on static analysis of technology-land productivities is quite common. Many previous studies ignore the dynamics of land productivity. This dynamic analysis underlines the importance of panel data sets to measure these different types of innovations. Unfortunately, in Africa, particularly in Ethiopia, the study of land productivity dynamics has been hindered by a lack of panel data sets.

The association between adopting new technologies and land productivity is important for both descriptive and policy purposes. Moving into a high level of productivity may be constrained by not adopting new technologies such as fertilizer and improved seeds. Someone who is adopting new technologies now can reasonably expect increasing productivity next year and expect to be in a better position than someone who is not adopting technologies now (Alene, 2010).

Moreover, the types of policies needed to address low productivity may be different from place to place. If low productivity is more of a permanent phenomenon, then policies that focus predominantly on natural ways of antidotes that help people to manage their land to increase the yield level of the plot are more appropriate (Kosmowski et al., 2020b; Wiredu et al., 2010). These include, among others, applying compost, manure, weather-dependent plowing, and other natural ways of preserving methods. By contrast, in a country where a significant proportion of the land is fertile and land productivity is a temporary phenomenon, then policies that address concerns of a more technological, such as applying fertilizer, adopting improved seeds, pesticides, herbicides, and others will be necessary (Morris, 1999; Wiredu et al, 2010; Bold et al, 2017).

The analysis of long-term vulnerability to low productivity is more relevant to policy than the analysis of productivity itself. Alene (2010) argues for increased attention to the quantification of vulnerability to low productivity for the important reason that vulnerability and risk are increasingly shown not to be just another dimension of low productivity; it is also a cause of low productivity. The World Bank is now supporting the economic development and use of Risk & Vulnerability Assessments (RVAs), which aim to investigate the sources of vulnerability and identify policy gaps. Quite recently, the investigation and measurement of vulnerability to low productivity have become an active area of research (World Bank, 2018).

Even though productivity improves in Ethiopia over time to time, vulnerability to low productivity due to the application of new technologies remained high (World Bank, 2015). Households are still prone to risks and shocks that cause them to slip back into poverty or remain in it due to low productivity (Twigg, 2004). In Ethiopia, the insurances given to crop production are so limited and household production outcomes fluctuate over time. So, the analysis of vulnerability is now demanding if only to design effective interventions towards sustainable development. Nevertheless, the vulnerability of rural farmers in Ethiopia has been measured in only a limited study (e.g., Lirenso, 2001; Temesgen et al, 2008; Tessema and Simane, 2019). Thus, this study tries to answer the following key questions. What is the role of adopting new technologies on land productivity in Ethiopia? Which technology practice can significantly increase land productivity in Ethiopia? Does recent technology adoption improve household vulnerability to low productivity in Ethiopia?

This study contributes to the literature on land productivity in three ways. First, it uses the recent measurement error-free three waves of the Ethiopia Socioeconomic Survey (ESS) panel data to analyze the nature of productivity among rural households. Such panel data sets give more information, degrees of freedom and efficiency, variability, and better power properties of the testing procedures (Verbeek, 2004). Thus, it contributes another panel study to the scanty set of studies on land productivity in Ethiopia. Second, it will fill the gap in the study of household vulnerability to low productivity in the future. Studies that explicitly consider vulnerability are quite a few in Ethiopia and given their valuable contribution to policymaking, there is an unsatisfied demand for studies on this area. Hence, this study attempts to explore vulnerability to low productivity in rural Ethiopia, using a recent crop-cut panel dataset. Third, the majority of empirical studies didn't capture the dynamics of land productivity. So, this study will capture all the above problems using thorough data and methodology.

1.3 Objective of the study

1.3.1 General Objective

The general objective of the study is to analyze the impact of adopted new technologies on land productivity in rural Ethiopia.

1.3.2 Specific Objective

- To examine whether the adoption of technologies improve land productivity.
- To quantify household vulnerability to low productivity
- To identify the best practice from different types of technologies and estimating the risk of technologies and the probability of increasing productivity.

1.4 Significance of the study

This study will contribute to a better understanding of the various innovations applied to land in rural communities. This endeavor has a major significance for productivity targeting specifically land productivity. Identifying households that are highly vulnerable to low productivity due to the adoption of agricultural technologies will help to design a more effective and efficient approach to increase land productivity. Since households that have saline or sloppy land are likely to need a different set of policies than those having fertile lands. The study also intends to investigate vulnerability even in households having fertile land. Moreover, Federal or Regional governments and policymakers are typically more interested in the future effects of the measures they take in relation to promoting the adoption of different innovations. For this reason, it is essential to identify those who are expected to be vulnerable in the future.

1.5 Scope and Limitation of the study

This study is based on an ESS panel data comprising three rounds of household survey spanning the period 2011/12 to 2015/16. This study has also its own potential limitations. First, it only includes rural areas in which urban agriculture is excluded. Second, Panel fixed effect estimation may not solve endogeniety even though we controlled many household, plot, and time characteristics. Third, when we measure vulnerability we use cross-sectional estimation which may have a limitation than using panel data. Finally, we measure land productivity as a crop yield in quintals and we didn't consider the impact of technologies on salinity of the land. Besides, further studies are required.

1.6 Organization of the Study

This study comprises in to five chapters. Introduction is presented in Chapter 1. Theoretical and empirical literature are reviewed is in chapter 2 Chapter 3 illustrate and discussed data and methodology. In Chapter 4 results and findings are discussed. Lastly, conclusion and policy implications are revealed in Chapter 5.

Chapter 2

Literature Review

2.1 Theoretical Literature Review

This section explores the theoretical concepts related to land productivity and technologies and their relationship including their broad explanations and measurement.

2.1.1 Definition and Concepts

Land productivity

Land productivity is the land ability or yielding to support and improve life which is "typically measured as physical output per unit of land, which is more simply termed as crop yield" (Gollin, 2018). Land productivity can be improved by uses of fertilizer inputs, uses of pesticides uses of extension programs, uses of manures, number of household size, the age of household sizes, and so on. 82% and above of the Ethiopian economy engaged in the agricultural sector directly or indirectly (CSA, 2012). So to increase the yielding of this agricultural sector we must increase the productivities of land.

Land productivity technologies

Land production technologies are technologies that include both biological and chemical technologies. Specifically, these technologies include fertilizers, improved seeds, hybrid seeds, irrigation, and soil quality-enhancing technologies. Farmers use these technologies to increase the productivity of the land and the yielding levels of land. This indicates that for poor farmers adoption of technology gets new demands on their scarce resource base (Kamruzzaman and Takeya, 2008). In general, more of the literature on agricultural technology adoption use the word 'technology' refers to fertilizer, improved germplasm, and other chemical inputs as well as agronomic practices, such as "integrated pest management" (Evenson and Gollin, 2003). The adoptions of more efficient farming practices and technologies that enhance agricultural productivity and improved environmental sustainability are instrumental for achieving economic growth, food security, and poverty reduction.

Fertilizer

It can be defined as any artificial or natural substances that containing the chemicalized elements these elements are used to improve the productivity of plants, crops, soils, and land (Kosmowski et al, 2020 b). Fertilizers must be classified into two types these are old fertilizers like compost and manure and the modern types of fertilizers include chemical fertilizers that consist of one or more of the elements that are more important for nutrition's the elements are nitrogen, phosphorus, potassium, sulfur, magnesium, and calcium (Crawford et al., 2003).

African governments have promoted increasing the use of agricultural inputs in their own countries inspired by the Asian Green Revolution which was brought about by using high-yielding seed and fertilizer technologies (Crawford et al., 2003). Similarly, Vein et al. (2008) reported that the usage of inorganic and organic fertilizer because, if soil fertility is not improved, the need for other technologies will not have a significant impact on land production.

The recent research indicated the application of inorganic fertilizers in Sub-Saharan Africa (SSA) is very low (DeJanvry, 2010, Freeman & Omiti, 2003). For instance, DeJanvry (2010) stated that the utilization of fertilizer in Sub-Saharan Africa (SSA) is only 11 kg/hectare compared to 130kg/hectare in South Asia and 271 kg/hectare in East Asia. The application of fertilizer in SSA is considered as the lowest rate in the overall of the world (Gornal et al., 2010).

This is a clear indication of the African agricultural development challenged because the fertilizer application in a hectare of land in SSA is below the standard (Crawford et al., 2003). The insufficient use of fertilizer in Africa has resulted in the area's productivity being below the world average (Morris et al, 2007; Kuhn & Gandonou, 2010).

The major reasons for low fertilizer use in SSA could be because of demand and supply factors (Crawford et al., 2003). On the demand side, the households that are working on the farm may not accept the profitability of using fertilizer; alternatively, they may accept it as profitable but too risky in financial terms. There is also uncertainty because the level of fertilizer input is determined before the rainy season which may be too risky for farmers. For instance, positive expectations about the rainfall conditions of the coming season lead to increased chemical fertilizer application by 41.92 kg/ha in Eastern Ethiopia (Fufa and Hassan, 2006). The uncertainty about the weather condition harms the yield-increasing inputs as they are unprofitable in the absence of enough rain (Morris et al., 2007). Possible reasons for the unprofitability could be attributed to low yield responses because of agro-ecological conditions, unresponsive seed varieties and fertilizer utilization, and high transportation costs for inputs and outputs (Crawford et al., 2003).

On the supply side, there is a high cost between the importers and local manufacturers or the farmers which may limit the access to fertilizer uses (ibid, 2003). Besides, the supply of fertilizer is affected by, inadequate arrangements for financing the purchase of fertilizer by importers and traders, poor port, rail and road infrastructure, transportation costs, and non-competitive behavior of the suppliers (ibid, 2003).

The production season is the factor to assume the risky for input utilization only in good times does taking risks to increase net outputs (Dercon and Christiaensen, 2010). For this reason, the farmers should be empowered to make their own decisions on how to use the fertility of their land (Morris et al., 2007).

There are also views that the dependency on chemical fertilizers only for agricultural production might not be sustainable as it results in the depletion of organic soil contents thereby reducing the potential benefit of fertilizer utilization (Ghosh, 2004). Most of the time, the application of chemical fertilizers is not based on soil tests which lead to the utilization of fertilizer either above or below their requirements (Ogoke et al., 2009). Moreover, (Waithaka et al., 2007) found that, in western Kenya, extension agents did not recommend the use of di-ammonium phosphate (DAP) by farmers because it aggravates the acidity of the soil. If chemical fertilizer application is not controlled and is used more than required, it could result in soil contamination and water pollution (Wu, 2011). The wise farmer knows the good fertilizers for the plants and the soil type of the plot area.

Pesticides

Pesticides can be explained as the collections of minerals or substances that are intended for destroying, preventing, and mitigating any pests on the land. To make agriculture profitable and more productive in the face of increasing costs and increasing standards of environmental and human health, using the best combination of available technologies to increases the yield level per unit of area can be attributed to more efficient control stress rather than an improvement in the yield potential. In some regions productivity of crops may be improved by high-yielding levels, improving water and management of soil, fertilization of land, and other new cultivation techniques. An improved level of crops, however, is often related to higher vulnerability to pest attack leading to increasing absolute reduction and the reduction rates (Oerke et al. 1994).

Improved seeds

Improved seed improves like yielding, the resistance of the pest, the tolerance of herbicide and drought, and more are of good for the farmers in an improved seed. The uses of improved seeds are critical agricultural input that helps farmers to obtain improved agricultural yields. The productivity and yields of crops are improved through the genetic manipulation of selective breeding (Sassenrath et al., 2008). Seeds that fulfill the quality requirements have a positive impact on the productivity of the land. Li et al (2010) found that 30 percent of the growth rate of agricultural production was due to new seed varieties.

Improved seeds will have a significant impact on the output and generally provide a more consistent result using improved seeds have benefits Because they are the best of the bunch, more seeds will emerge, therefore less seed is needed, which saves the money, Seedlings from high-quality seeds will be strong and produce uniform plants, Plants will grow faster shortening the time from planting to harvesting, Seeds of higher quality are more resistant to disease and distress, Crops will produce a more uniform and robust end product that will demand a higher price, improved seeds have more vigor (diseases control). Furthermore, Alemu et al (2008) stated that improved seeds can cause a remarkable improvement in agricultural productivity and production for small-scale farmers in Ethiopia if they are combined with modern science and modest changes in farmers' cultivation practices. As the improved seeds are small, farmers are more concerned about the characteristics of the seeds rather than the price (Li et al, 2010).

Herbicide

It is a pesticide type that is normally good for killing unwanted plants like weeds and it is used for weed controls in places where the laborers worked on the farm are scarce and to minimize the cost paid for the labor. There are different types of herbicides based on the period of application on the farming time. The first one is the application of the herbicide before the sown of the corps on the farm which is called pre-plant which kills the weeds before planting. The second one is applied on the farm which is before the growth of weeds which is called pre-emergence. The last one is applied after the growing of weeds occurs which is called post-emergence.

Fungicides

Fungicides are the types of pesticides that are used to kill and prevent the growth of fungi that kill plants including rust mildews and blights. They might also be used to control mold and mildew in other settings. It has a role in the protection of fruits, vegetables, saving standing crops, stress, ornamental plants.

On top of these, some variables determine land productivity such as health (which is measured using ADL index), compost, plot slope, and productive safety net programme. In this study, we bring all of the above variables into the regression analysis.

Considering some other explanatory variables

Irrigation

Water is one of the good instruments of poverty eliminates, plays a significant role in food production, food security, sanitation, and environment protection (Hussain and Hanjra, 2004). The proper usage and the minimization of wastage of water resources are critical. This is because the level of water consumption in agriculture is influenced by the efficiency of irrigation systems and cultivation methods used by farmers (Castro and Heerink, 2010). For instance, implementing a system of water trading can reduce the amount used in agriculture all at once and distribute by the rightful owner (De Janvry, 2010). Irrigation is one of the major inputs in land productivities that benefit the socio-economic status as it leads to poverty reduction. When such types of problems cause disease, land degradation, water pollution, and destruction of living beings and natural ecosystems the poor populations are affected negatively by irrigation. (Hussain & Hanjra, 2004). But access to good irrigation allows the poor to increase production, gives them opportunities to diversify their income base, and reduces their vulnerability to low productivity and shocks (Hussain & Hanjra, 2004).

Crop rotation

Is a mechanism of cropping many types of crops in one plot of land across respective growing seasons It is more important than monocropping because it increases the fertility or the yielding of the land, it is used to the optimized nutrient of soil and it increases the yielding levels of crops and/or regularly recurrent succession of many crops on the same plot area (Tulu, 2011). It helps to the required fertility of the land and controls weeds and diseases of plants through the appropriate application of crop orders (Knox et al, 2011). It is used to improve the structure of the soil; it helps to recover soil nutrients and reduces the usage of fertilizers on the plot area.

Extension service

Extension services are an important element to link market and nonmarket entities and agents that provide human capital-enhancing inputs, as well as flows of information that can improve farmers' and other rural peoples' welfare; importance long recognized in development dialogue

(Anderson et al., 2003). The reason that the extension service includes the transferring of knowledge from researchers or the educated persons to farmers, giving information for the farmers in their decision making and teaching the farmers on how to make good decisions to achieve their own goals and any chance to make their Land productive (van der Ban and Hawkins, 1996). While extension agents often also provide services that are not directly related to land productivities e.g., health, non-farm business management, and nutrition.

Household size

Household size is essentially the number of persons for whom you are financially or by any means responsible for land productivity and the yielding levels of the farm. If the member of household size increases the productivity of land and their yielding is increasing. As the number of household members increases land productivity also increases the reason is that the rural household of Ethiopia uses more family labor than any other labor in their farm production processes. So the land productivities and their yielding is depended on the household sizes.

Land ownership certificate

Land certificate is ownership right for using land to improve efficiency and making long-term investments on their land. If farmers have their land which is certificated by the government makes farmers more productive than farmers who do not have their land, because the owner farmers invest short term and long term plants as farmer convince that is useful for improving their land productivities and the yielding levels but the non-certified farmers do not use any long term investments and also have another cost for renting the farm.

Numbers of plots and soil quality

The numbers of plots are the plots that the farmers used for agricultural productivity. In Ethiopia, the average farm size is less than one hectare which is 0.9 hectares (FAO, 2015). Soil quality is the naturally gifted capacity of soils for giving good yields in the farmland. This quality is a characteristic of soil and varies from soil type to soil type and it consists of organic matters these are, salinity, nutrients, and rooting depth help to protect the health of the soil. For example, organic-matter content, biological activity, acidity, and salinity are related to the ability of a soil to store and cycle nutrients for plant growth and it contributes for sustainability. However, if the ability of a soil to perform beneficial functions has been impaired, the quality or condition of that soil has been degraded and that land use detracts from the sustainability of the soil resource.

Labor

Labor may be family, shared, or hired labor. Family labor is a worker from the farm family itself. Shared labor is an alternative to layoffs that may be used when the work available especially on the farming system work is seasonal so the labor is not enough at that time used the shared labor to cover on time and reducing the working hours this is good for land productivities and the yielding levels. Hired Labor is an employment type which is agency workers, temporary staffs or outsourcing a business recruitment process to a third party. They take care of the entire hiring process, including payroll, pension, tax, and ensure that the hired labor provided meets the rights and expectations of the client company.

2.1.2 Linking Agricultural Technologies and Land Productivity

Based on the review of the vast literature on productivities of land and adoption of technologies, we investigate the following theoretical framework for this study. Fertilizer and pesticide both are plays important roles to increase land productivity because the fertilizers contain the nutrients that are used for plants growth, so the farmers use a suitable amount of chemicals and biological-fertilizers. Because applying too many amounts of fertilizers will not result in higher yields. On the contrary, it reduces the yielding level of the land. Therefore, to increase the land productivity the farmer must apply fertilizers in an adequate amount according to the types of crops, soil type, and previously added fertilizers on that plot area, additionally pesticide is a good technology to improved land productivity by voiding all insects and fungus. As many studies argued that crop rotation and intercropping have a positive effect on land productivity because applying these on land can increase the number of cultivated crops per year and per hectare, at the same time it provides an adequate use of natural resources than the monoculture cultivations.

Hybrid and improved Seeds are the key inputs for increasing crop production and land productivity because increasing the quality of seeds can increase the yield level of the crops on the given plot area. Appling improved and hybrid seeds are good for agricultural development particularly land productivities for Ethiopia because the Ethiopian economy is engaged in agriculture (Atilaw & Korbu, 2011). Other technologies are used to improved agricultural implements such as power tillers or tractors. Thus, the scientific process of cultivation will help the farmers to increase the yield of crops per hectare. In agriculture, some types of soil would be better for the cultivation of rice than wheat. Therefore to increases land productivity, the farmers must identify the soil type suitable for the cultivation of a particular crop. Generally, the productivity of land is largely determined by the natural qualities of the land and applied technologies.

2.2 Empirical Literature Review

Many studies have attempted to examine the impact of new technology adoptions on productivity. Among these Barmon et al (2007) investigated Agricultural Technology Adoption and Land Productivity from Rice-Prawn Gher (RPG) Farming System in Northern Bangladesh. They find that the RPG indigenous farming system has significant impacts on inputs used in rice production. The findings of the study also indicates that more chemical fertilizers were used in per hectare rice production under year-round modern varieties (YRMV) rice farming in comparison with RPG farming. Therefore, it could be concluded that land productivity varies widely between the two farming systems and the adaption of technologies should be different in different settings of farming systems.

Wiredu et al (2010) assessed the effect of improved technology on land productivity of smallholder cocoa farmers in Ashanti Region, Ghana using 366 smallholder cocoa farmers. They found that productivity was found to be linearly related to the use of improved cocoa technology in the study area. Productivity is also determined by the decision to apply improved technologies and land used for cocoa production. Besides, farm-level factor characteristics, idiosyncrasies are shown to affect productivity. These including participation in programs related to cocoa production, access to virgin lands, size of the cocoa farm, age, household size, labor resource use, and negativity that affect productivity at various levels of significance. Strategies to enhance smallholder cocoa farmer's productivity must contain the promotion of improved cocoa technologies as it improves the land productivity of these smallholder farmers.

González et al (2009) used a dataset gathered by the Program for Technological Support in the Agricultural Sector (PATCA) to evaluate the impact of agricultural extension services in the Dominican Republic. The data included 1,572 farmers participating in crop growing, breeding, or milk production. By applying a propensity score matching method, they found that the technologies supported and financed through PATCA efficiently enhance the productivity of rice producers and breeders. However, they did not find any significant impact on other producers. These heterogeneities could be due to the varying level of effectiveness of the promoted technologies in the short run, where land pasture conservation and leveling could be the fastest in showing significant effects. Moreover, they did not find any clear evidence that the PATCA program had a significant impact on the production quality that was reflected in prices reported by farmers.

Miss & Mohammed (2016) also examines the impact of technology adoption on agricultural productivity in Bangladesh by randomly selecting 60 rice farmers. This study finds sufficient variation in frequency and degree of technology adoption in agricultural practices among the surveyed farmers. The analysis results indicate that farmers are adopting high level of technology in seed variety and irrigation phases, medium level of technology in land preparation, pest management and fertilizer application phases and low level of technology in weeding and harvesting phases. There is a statistically significant difference in productivity between high and low degree technology adopters. And they concludes that there is a scope for further increase in productivity through planned manipulation of technology adoption level in different phases of agricultural production.

Few studies have analyzed the impact of the newly emerging technologies on land productivity in Ethiopia. Tessema (2015) used the Ethiopian socio-economic survey(ESS) of 2011/12 and 2013/14 to investigated the determinants of farm income and agricultural productivity in Ethiopia by applying fixed effects, Pooled ordinary least square, and the random-effects model. His result showed that the use of fertilizer, Land-labor ratio, use of pesticide, manure, and household size are the most significant variables that affect land productivity. However, the productivity of land is negatively affected by droughts. The study also explores the farm income determinants in which the dependency ratio is significantly and negatively affects the income of rural households. This study recommended that adding a land-labor ratio is good for agricultural productivity enhancement and agricultural income improvement.

Wordofa et al. (2021) investigate the adoption of improved agricultural technologies in eastern Ethiopia. They investigates the impact of improved agricultural technology use on farm household income in eastern Ethiopia using Primary data for the study was obtained from a random sample of 248 rural households, 119 of which are improved technology users and the rest are non-users. The research employed the Propensity Score Matching (PSM) procedure to establish the causal relationship between adoption of improved crop and livestock technologies and changes in farm income. There Results showed that households using improved agricultural technologies had, on average, 23,031.28 Birr (Birr is the official currency of Ethiopia. Adopters have higher annual farm income compared to those households not using such technologies. Their findings highlight the importance of promoting multiple and complementary agricultural technologies among rural smallholders. They suggest that rural technology generation, dissemination and adoption interventions be strengthened. Moreover, the linkage among research, extension, universities and farmers needs to be enhanced through facilitating a multi-stakeholders innovation platform.

Ersado et al (2004) also examine productivity and land enhancing technologies in northern Ethiopia with a special emphasis on health, public investments, and sequential adoption using data from World Health Organization. Their findings from a multinomial logit model suggest that agencies working to enhancing agricultural productivity and conservation of land resources should consider not only the financial status of potential adopters but also their related health situation. The empirical tests of the study also demonstrate strong evidence supporting the importance of accounting for sequential adoption.

Biru et al (2020) examines the impact of multiple complementary technologies adoption on consumption, poverty and vulnerability of smallholders in Ethiopia. The study used a balanced panel data obtained from a survey of 390 farm households collected in 2012, 2014 and 2016. They employe two stage multinomial endogenous switching regression model combined with the Mundlak approach and balanced panel data is employed to account for unobserved heterogeneity for the adoption decision and differences in household and farm characteristics. They find that the adoption of improved technologies increases consumption expenditure significantly and the greatest impact is attained when farmers combine multiple complementary technologies. They conclude that the adoption of multiple complementary technologies has substantial dynamic benefits that improve the welfare of smallholders in the study area, and given the observed low level of adoption rates, we suggest that much more intervention is warranted, with a special focus on poorer and vulnerable households, to ensure smallholders get support to improve their input use.

Overall, the empirical works of literature reviewed reveal several facts and justifications about the adoption of new technologies and land productivity. First, beyond the statistical trend, the empirical findings in the literature, based on a large sample, in general, indicate a positive relationship between adopted technologies and land productivity (see Wiredu et al (2010); González et al (2009); Barmon et al (2007)). Second, the productivity of land is determined by many other variables. For example, Asfaw and Admassie (2004) reported education level of farmers is very important for land productivity. Studies have also indicated that female farmers are more environmentally good compared to male farmers (Burton, 2013). I am motivated by this study to investigate the productivity differences between male and female-headed households. In this respect, researchers found mixed results. In the study conducted in China, de Brauw et al (2013) showed that female-headed households achieved the same crop yield as their male counterparts. In the survey conducted in the four major regions of Ethiopia (Tigray, Amhara, Oromia, and SNNP), (Ragasa et al, 2013) established that, if other influencing factors were constant, there was no productivity difference between female-headed farmers and male-headed farmers.

Moreover, land productivity is also influenced by other household characteristics such as the farm household head age, family size, and landholding size. The age of the household head is a proxy variable for the farming experience of farm operators. Farmers are highly dependent on their previous knowledge of farm practices in cultivating different crops. Farmers who have a lot of experience are expected to improve productivity; however, older farmers haven't adequate physical strength and a lower likelihood of technology adoption (Moussa et al, 2011; Burton, 2013). Sometimes, it is thought that small land size is more productive than large farms and it is recommended that strategies of agricultural development need to be backing of small farms rather than large farms. Scholars in the field (Venkatesan & Kampen, 1998) suggest that raising agricultural production in the fixed land could only be achieved by raising the yield and productivity of farm labor, yet it is mandatory for developing countries to innovate and adopt appropriate technologies.

Furthermore, household possession of oxen also determines the land productivity of farmers because if farmers do not have oxen they would be obliged to rent out their land or plot area to other farmers or oxen owners (Holden et al.,2004). In this case, farmers would enter into sharecropping. Household income and production will further diminish as oxen owners shared the yield. There are advantages associated with owning oxen. Oxen owners can cultivate and sow their land at the right time and sow the seeds that are suitable to their lands and the season in that time.

Chapter 3

Data and Methodology

This section describes the overall methodology of the study, model variables and the source of data, methods of data analysis and empirical model specification with briefly explanation beneath.

3.1 The Data Set

This study wills employ the three rounds of the Ethiopian Socioeconomic Survey (ESS) crop-cut panel data. The ESS is a collaborative effort of the World Bank's Living Standards Measurement Study (Integrated Surveys of Agriculture program/ LMESA) and Central Statistical Agency of Ethiopia (CSAE). The first round of the ESS survey (ESS1) covers only rural and small-town places and the second and third round survey (ESS2 &ESS3) covered and explored urban areas. The third wave of the ESS survey (ESS3) was conducted by including urban dwellers to make the data countrywide representative. Hence, the collection of ESS1, ESS2, and ESS3 create a panel data set of households from rural and small-town areas, whereas ESS2, and ESS3 together represent a panel of data set for rural, small town, and all urban areas. So, this study investigates its objective based on a panel of households from all three surveys, the small town and urban sample is automatically excluded. Therefore, this study concentrates on rural areas to decrease heterogeneity in the analysis.

The first wave of ESS started in 2011 with rural and small-town of 3776 households. The number of enumeration areas (EAs) covered by the survey increased from 333 (or 3,776 households) to 433 (or 5,262 households) in the second (ESS2) and third wave (ESS3). This Ethiopian socioeconomic survey used a stratified sampling, a two-stage sampling design, where the Ethiopian regions were considered as the strata from which enumeration areas were chosen proportionally based on the population size of regions. The variables which will be used in the study are presented in Appendix A.

3.2 Methods of Data Analysis

This study will use descriptive and econometric analysis tools. Panel fixed estimation, Quantile regression, and Probit regression will also be adapted to analyze the data.

3.2.1 Empirical Model Specification

Based on the neoclassical production function the model can be specified on the following settings. Letting Y measures the yield level from a given plot of land, X represents technologies adopted by farmers, L represents labor working on the plot of land, and Z represents other included explanatory variables; the model in the setting of neoclassical production function can be formed as:

$$Y = f(X, L, Z) \tag{3.1}$$

Taking natural logarithmic on both sides of standard Cobb-Douglas production function, then controlling for household-fixed effect and time-fixed effect, we have:

$$LnY_{ipt} = \alpha LnX_{ipt} + \beta LnL_{ipt} + \varphi LnZ_{ipt} + \mu_i + \lambda_t + u_{ipt} \tag{3.2}$$

All available data on farm inputs and output are plot level, so Y_{ipt} stands for farm output for household i, on plot p and at time t, while μ_i are unobservable time-invariant household-fixed effects, λ_t is year-fixed effects, and u_{ipt} is the random error term. α, β, and φ are output elasticity.

3.2.2 Measuring Vulnerability

Using a threshold for low productivity we can use a model to measure vulnerability .Following Naude et al (2009) and Chaudhuri et al (2001), household vulnerability at time t is defined as the probability that the household will find itself in a risk of low production and poor consumption at time t+1:

$V_{ht} = Pr(P_{h,t} + 1 < m)$

Where $p_{h,t+1}$is the household's production level at time t + 1 and m is the appropriate production level in line with the consumption line. The main problem here is that $P_{h,t+1}$ is not directly observable. Chaudhuri et al. (2001) proposed a method for actually quantifying V_{ht}. The proposed method outlines the three required information to the measure vulnerability of households to different shocks: The household's expected level of production in the next period, the low production line (m), and the variance of the household's expected level of production in the next period (δ^2).

Even though the household's level of production for the next year is unknown, it is possible to arrive at an arguable estimate by first constructing a model of the determinants of production and then using the model to predict next year's production. Here we assume that the expected level of production level follows the normal distribution. Econometrically, we have a model of

$$lnP_h = E_h \varpi + U_h \tag{3.3}$$

where P_h is per capita consumption expenditure, E_h represents a bundle of observable household characteristics, characteristics such as household size, location, age, sex, educational attainment of the household head, etc., ϖ is a vector of parameters, and U_h is a mean- zero disturbance term that captures idiosyncratic shocks that contribute to different production levels for the household.

The model in 3.3 assumes that the idiosyncratic shocks to consumption are identically and independently distributed over time for each household. However, this is highly unlikely to hold for a single cross-section. Hence, we allow the variance of $U_h(\delta^2_{u,h})$ to depend upon observable household characteristics in some parametric way. We assume that the variance of uh is given by:

$\delta^2_{u,h} = E_h \vartheta$

ϖ and ϑ Are estimated using a three-step feasible generalized least squares (FGLS) procedure suggested by Jushan et al (2019). First, we estimate equation 3.3 using an ordinary least squares (OLS). We then use the estimated residuals from equation 3.3 to estimate

$$\hat{U}^2_{OLS,h} = E_h \vartheta + \tau_h \tag{3.4}$$

Using OLS the predictions from 3.4 can be used to transform the following equation as follows:

$$\frac{\hat{U}^2_{OLS,h}}{E_h\widehat{\vartheta}_{OLS}} = (\frac{E_h}{(E_h\widehat{\vartheta}_{OLS})})\vartheta + \frac{\tau_h}{(E_h\widehat{\vartheta}_{OLS})}$$

This transformed equation is estimated using Ordinary Least Square (OLS) to obtain an asymptotically efficient FGLS estimate, $\widehat{\vartheta}_{FGLS}$FGLS. Note that $E_h\widehat{\vartheta}_{FGLS}$ is a consistent estimate of $\delta^2_{u,h}$, the variance of the idiosyncratic component of household consumption. The estimates

$\widehat{\delta}^2_{u,h} = \sqrt{E_h\widehat{\vartheta}_{FGLS}}$

are then used to transform 3.3 as follows:

$$\frac{LnP_h}{\widehat{\delta}^2_{u,h}} = (\frac{E_h}{(\widehat{\delta}^2_{u,h})})\varpi + \frac{U_h}{(\widehat{\delta}^2_{u,h})} \tag{3.5}$$

OLS estimation of 3.5 yields a consistent and asymptotically efficient estimate of ϖ.

Using the estimates ϖ and ϑ that we obtain we are able to directly estimate expected log production:

$\widehat{E}\left[\frac{LnP_h}{E_h}\right]$=$E_h\widehat{\varpi}$

and the variance of log production:

$\widehat{Var}\left[\frac{LnP_h}{E_h}\right]$=$(\widehat{\delta}^2_{u,h})E_h\widehat{\varpi}$

for each household h. By assuming that production is log-normally distributed, we are then able to use these estimates to form an estimate of the probability that a household with the characteristics, Eh, will be poor, i.e.to estimate the household's vulnerability level. Letting $\phi(.)$ denote the cumulative density of the standard normal, this estimated probability will be given by:

$$\widehat{V_h} = \widehat{\Pr}(LnP_h < Lnm/E_h) = \phi\left(\frac{Lnm - E_h\widehat{\vartheta}}{\sqrt{E_h\widehat{\vartheta}}}\right) \tag{3.6}$$

Although the above method is not very informative concerning the effect of change in a given household and community characteristics on the probability of being vulnerable, it allows us to examine the vulnerability degree/extent of the household to low production.

Chapter 4

Results and Discussions

This section presents and discusses the main findings of the analysis of land productivity and new emerging technologies including other determinants of land productivity in rural Ethiopia based on the Ethiopian Socio economic survey (ESS) panel data set.

Table 4.1: Summary Statistics

VARIABLES	Mean	SD
Crop-cut yield level, in quintals	2.499	8.898
Total fertilizer application, in kg	7.579	26.21
Amount of improved seed application, in kg	4.218	13.59
Pesticide (1 if the used)	0.026	0.161
Herbicide (1 if the used)	0.111	0.314
Fungicide (1 if the used)	0.006	0.081
Plot size measured using GPS, in hectare	0.191	0.430
Irrigation Dummy (1=irrigated)	0.022	0.147
Total household labor used on plot, person days	11.69	14.72
Total hired labor used on plot, person days	4.286	73.85
Total labor used from other households, person days	1.650	6.741
Land Certificate (1=Yes)	0.618	0.486
Activity Daily living Index (ADL-Index)	23.77	1.172
Total number of Oxen	0.547	1.222
Household size	5.747	2.199
Head Sex	0.865	0.342
Age of the household head	49.00	14.31
Number of plots	2.449	2.629
Number of crops	1.119	0.415
Year of schooling	2.017	5.461
Proportion of Adult in a household	0.837	0.093
Read Write Dummy (1=Yes)	0.440	0.496
Plot Slope Dummy (1=sloppy)	0.106	0.308
Soil Quality Dummy (1 if good)	0.209	0.407
Productive Safety Net Programme (PSNP) Dummy (1 if participated)	0.045	0.207
Crop Rotation Dummy (1 if apply)	0.883	0.322
Extension Dummy (1 if received)	0.4923	0.049
Number of Observations=5415 & Number of Cluster=1739		

Source: Own Calculation from Ethiopian Socio-economic Survey (ESS)

As the above table 4.1, the number of observations of each variable is 5415 which is very high and it makes our sample proportionally representative and better than other prior studies (e.g. Ersado et al (2004); Tessema (2015); Moussa et al (2011); Burton (2013)). The average crop-cut yield is 2.499 quintals. The mean fertilizer application from 5415 households is 7.579 kilograms which tell us most of the farmers apply fertilizer to increase their harvest. Those households on average used 4.218 kilograms amount of improved seed. More than half of the households in the sample did not use pesticides, herbicides, and fungicides for their crop production. The average measured land use for production is 0.191 hectares with a standard deviation of 0.43. Furthermore, the average number of oxen, plots, and crops are 0.547, 2.449, and 1.119 respectively.

From table 4.1 we can also infer that more household farmers in rural Ethiopia have Land Certificate (61.8%) and apply Crop Rotation (88.3%). However, households in rural Ethiopia has a low level of irrigation (2.2%), more of them are uneducated in which the one who can use Reading and writing is 44%, very few (4.4%) households have participated in the Productive Safety Net Programme, and only 49.2% of the household get extension service from the government. The average household size is 5.747 and most of the household heads are Male (86.5%) and adult (83.7%). Among those 10.6% of households have a sloppy plots.

4.1 Estimation Results

Tables 4.2 show panel fixed effect regression of Cobb-Douglas production function under different specifications scenarios and set of controls. The first column in Table 4.2 shows the baseline specification results. In the baseline specification, we control for a limited number of control variables, which are recommended by the underlying farm production function. Column two in the same table also shows estimation from panel fixed effect of farm production function after controlling for additional continuous controls (i.e. number of plots, number of crops, household age, and household size) in addition to controls in the baseline model specification. The third column also presents the land productivity estimation result, which captures the available dummy household and plot characteristics in addition to continuous controls in column two. Our analyses heavily concentrate on the final column because we controlled available time-variant household and plot characteristics; therefore the specification is considered to be robust to omitted variable bias or/and possible endogeneity threat. Across all specifications scenarios, household-fixed effect, crop-fixed effect, and time-fixed effect are controlled.

Table 4.2: Panel Fixed Effect Model Estimation

	Panel Fixed Effect Model Dependent Variable: Log Land Productivity		
VARIABLES	1	2	3
Ln Fertilizer	0.115*** (0.0110)	0.115*** (0.0110)	0.116*** (0.0111)
Ln Improved Seed	0.132*** (0.0181)	0.129*** (0.0183)	0.128*** (0.0184)
Pesticide	−0.109 (0.0795)	−0.112 (0.0794)	−0.110 (0.0801)
Herbicide	0.0516 (0.0406)	0.0456 (0.0407)	0.0452 (0.0407)
Fungicide	0.378*** (0.139)	0.379*** (0.140)	0.381*** (0.141)
Compost	0.0126 (0.0487)	0.00900 (0.0481)	0.0151 (0.0483)
Ln Household Labor	0.151*** (0.0139)	0.149*** (0.0142)	0.150*** (0.0142)
Ln Hired Labor	0.136*** (0.0183)	0.134*** (0.0186)	0.132*** (0.0186)
Ln Shared labor	0.121*** (0.0186)	0.113*** (0.0187)	0.113*** (0.0187)
Land certificate	−0.0846* (0.0483)	−0.0879* (0.0482)	−0.0852* (0.0475)
Ln Oxen	0.0814 (0.0508)	0.0801 (0.0507)	0.0949* (0.0502)
Ln ADL_index	0.110* (0.0632)	0.113* (0.0661)	0.0995* (0.0596)
Ln Number of Plots		−0.0851*** (0.0222)	−0.0858*** (0.0225)
Ln Head Age		0.258 (0.199)	0.231 (0.196)
Ln Household Size		−0.148* (0.0875)	−0.157* (0.0912)
Ln Number of crops		0.124 (0.0830)	0.120 (0.0829)
Irrigation Dummy			0.0264 (0.107)
Plot Slope Dummy			0.0586 (0.0391)
Soil Quality Dummy			0.0230 (0.0328)
PSNP Dummy			−0.00552 (0.0775)
Head Sex			0.106 (0.248)
Crop Rotation Dummy			0.123* (0.0688)
Extension Dummy			0.0388 (0.0382)
Read Write Dummy			0.00492 (0.0538)
Constant			−0.830 (0.875)
Observations	5,415	5,415	5,415
Number of cluster	1,739	1,739	1,739
R-squared	0.282	0.287	0.289
Household FE, Year FE & Crop FE	Yes	Yes	Yes

*Key: *** p<0.01, ** p<0.05, * p<0.1 shows statistically significant at 1%, 5%, and 10% level respectively. Standard errors are in parentheses.*

Source: Author Computation from Ethiopian Socio-economic Survey (ESS)

Table 4.2 presents the results of panel fixed effect regressions on household determinants of land productivity. The dependent variable is total crop production or harvest. According to the results, as reported in Table 4.2, Fertilizer, improved seed, pesticide, fungicide, and herbicide used has an impact on land productivity in all three regression model specifications. The fascinating point in this regression is the magnitudes and significances of the coefficients of technology variables are less sensitive in affecting land productivity when controlling for additional covariates in columns two and three. However, there is some little improvement and decrement in the magnitude of coefficients. All technology parameters are positive except pesticide in which harms land productivity although it is insignificant. Fertilizer, Improved seed, and fungicide are highly significant variables to increase yield level. Overall, applying technologies on the land improves the productivities of land. As most of the literature argues that technology adoption is imperative to enhance land productivity, our estimate reveals that most of the technologies such as fertilizer, improved seed, and fungicide have a statistically significant impact on crop yield or harvest.

Furthermore, the coefficients on each major farm input such as family labor, hired labor, and shared labor are highly significant and positive across all the three specifications. Moreover, using compost is also an important variable for the rural household labor productivity enhancement, which shows that, the land productivity increases by 0.0151 units as the farm households use compost for their farm production process in one production period. This implies that animal dung is very important as the chemical fertilizer may not be affordable for some poor rural farm households.

The coefficients of additional continuous control variables such as the number of plots and household size are found to have statistically significant. Surprisingly, as the number of household size increases by one percent the land productivity of the household declines by 0.157 percent and it is also it is significant at a one percent level of significance. One known reason behind this is that the rural household of Ethiopia uses more family labor than hired labor in their farm production processes. As a result, having more labor within a household would be able to a high possibility of farm management work to increase farm output.

Furthermore, except for crop rotation, the coefficient of each categorical dummy household and plot characteristic is not statistically significant. Even though the coefficients on those additional controls are statistically insignificant, the inclusion of such controls brings a little improvement on coefficients of the technology indicators. It implies that there is a possibility of a downward bias on the coefficients of the technology indicators in the case where those controls are omitted from the model as the coefficients of the technology indicators are a bit smaller in column one. And health condition measured by ADLI is found to have a statistically significant impact on land productivity in all specifications. This implies that a healthy family can improve land productivity.

The use of extension service also increases the farm household labor productivity by 0.0388 units as the households were got the service during one production season of the survey period. It is also consistent with the finding of Asres et.al (2013) in Ethiopia, during their study of the Effect of agricultural extension programs on small holder's farm productivity. Therefore, expanding and encouraging the farm household participation rate for the use of extension service is still important for the land productivity enhancement since the extension user households are more productive than non-users households. Irrigation has a positive impact on land productivity. An irrigation system or any other source of water is also useful during the drought season to increase the land productivity of rural farm households. This implies that rain-dependent agriculture is risky for farm household labor productivity enhancement.

We also disaggregate our results by the sex of the household head (See Appendix B). Under all model specifications, land productivity effect of technology application and adoption seems positive and the same across all households expect for a pesticide for both sex. The coefficient of Fertilizer appears highly significant in all specifications for all gender of the household head, however, the improved seed is surprisingly found to have insignificant under female-headed household regression. Moreover, the coefficients of additional continuous and dummy controls are statistically insignificant for both gender but crop rotation is significant for male-headed household under all specifications. This may be a sampling difference between male and female-headed households (male has 4685 and female has 730 observations).

Table 4.3: Determinant of Land Productivity at Various Quantiles

	Dependent Variable: log Land Productivity			
VARIABLES	25 Quantiles	50 quantiles	75 quantiles	85 quantiles
Ln Fertilizer	0.0488***	0.0654***	0.0776***	0.0615***
	(0.00609)	(0.00822)	(0.0114)	(0.0137)
Ln Improved Seed	0.145***	0.181***	0.219***	0.233***
	(0.0119)	(0.0161)	(0.0222)	(0.0268)
Pesticide	−0.0501	−0.115*	−0.158*	−0.130
	(0.0474)	(0.0641)	(0.0885)	(0.107)
Herbicide	0.0470*	0.0800**	0.220***	0.244***
	(0.0258)	(0.0349)	(0.0481)	(0.0581)
Fungicide	0.342***	0.579***	0.589***	0.604***
	(0.0942)	(0.127)	(0.176)	(0.212)
Compost	−0.0217	−0.0633	−0.0464	−0.0873
	(0.0336)	(0.0454)	(0.0627)	(0.0756)
Ln Household Labor	0.0946***	0.148***	0.189***	0.191***
	(0.00768)	(0.0104)	(0.0143)	(0.0173)
Ln Hired Labor	0.108***	0.155***	0.156***	0.164***
	(0.0104)	(0.0140)	(0.0193)	(0.0233)
Ln Shared labor	0.0626***	0.101***	0.145***	0.170***
	(0.00921)	(0.0124)	(0.0172)	(0.0207)
Land certificate	−0.0846*	−0.000119	−0.0184	0.00236
	(0.0160)	(0.0216)	(0.0298)	(0.0360)
Ln Oxen	0.126***	0.231***	0.335***	0.327***
	(0.0218)	(0.0294)	(0.0407)	(0.0490)
Ln ADL_index	0.0995**	0.123*	0.192**	−0.0117*
	(0.0501)	(0.0676)	(0.0933)	(0.113)
Ln Number of Plots	−0.0751***	−0.142***	−0.227***	−0.247***
	(0.0150)	(0.0203)	(0.0280)	(0.0338)
Ln Head Age	0.0274	0.0605*	0.00901	0.0699
	(0.0257)	(0.0347)	(0.0480)	(0.0579)
Ln Household Size	0.0152	0.0371	0.0886**	0.111 ∗ ∗
	(0.0213)	(0.0287)	(0.0397)	(0.0479)
Ln Number of crops	−0.114**	−0.108	−0.150	−0.146
	(0.0543)	(0.0733)	(0.101)	(0.122)
Constant	−0.260	−0.277	0.0600	0.701
	(0.196)	(0.265)	(0.366)	(0.441)
Observations	5,415	5,415	5,415	5,415

*Key: *** p<0.01, ** p<0.05, * p<0.1 shows statistically significant at 1%, 5%, and 10% level respectively. Robust standard errors are in parentheses.*
Source: Author Computation from Ethiopian Socio-economic Survey (ESS)

According to the results, as reported in Table 4.3, adoptions of technologies have a positive and significant effect on land productivity except for pesticides even at different quintiles. But pesticide is significant at 50th and 75th quantile regressions. Household labor of the household head has a positive and highly significant impact on land productivity. Shared labor and hired labor are also associated with high productivity. Health is highly significant in increasing land productivity. The number of the plot is negatively associated with land productivity. Similarly, households with more oxen are highly likely to have high land productivity. The household that has many crops has a negative impact at a lower quintile but it has a positive impact at the higher quintile.

Four things are worth noting about the panel fixed effect estimation and quantile regression results. First, technologies like fertilizer, improved seed, and fungicide increase land productivity significantly. Second, we controlled heterogeneity as maximum as possible. We also include household fixed effect (FE), Year FE, and Crop FE where other studies only control household FE and Year FE. Third, we controlled endogeneity by using the fixed effect panel modeling controlling. Our results are consistent with what previous studies have found (see Tessema (2015); Asfaw and Admassie (2004); Wiredu et al (2010); González et al (2009); & Barmon et al (2007)). So these critical observations have important policy implications in dealing with emerging new technologies and land productivity links. Fourth, other variables like health conditions measured by ADL Index have a great contribution for land productivity improvement in all scenarios and quintile regression. Therefore, health reform is needed.

4.2 Vulnerability Estimation and Sources of Vulnerability

As discussed in chapter 3, the technique by Chaudhuri et al. (2001) is applied to estimate a household vulnerability index. First, we calculated a household's expected production and variance of it. To do so, we follow three-step feasible generalized least squares (FGLS) estimation procedure to allow for heteroscedasticity in estimating the expected value and variance of production following Amemiya's (1977) and Kasirye (2007). The results are reported in Appendix C.

As showed in Appendix D, the fitted values of the regression from the last stage were used as an estimate of expected mean production and the fitted values of the second stage regression were used as the variance. As adopted from procedure by Chaudhuri et al. (2001) assumes that the expected level of production follows the normal (Gaussian) distribution. A Kernel density graph of predicted log production was constructed to test whether this assumption is fulfilled and this is provided in Appendix D. Comparing this with the Gaussian distribution curve, it is reasonable to infer that the estimated expected production is log-normally distributed. Thus the estimates of the expected value and variance of production from the FGLS regressions were used to generate an index of household vulnerability as specified in 3.4.

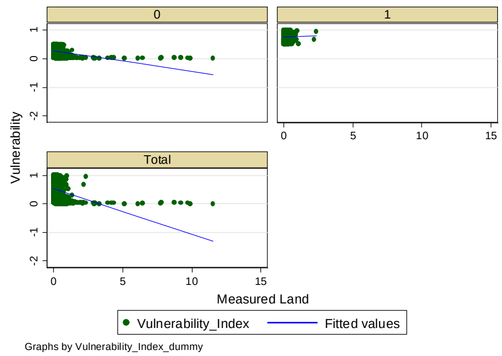

Figure 4.1: Vulnerability and Measured Land of Households
Source: Own computation from ESS Data

As we can observe from Figure 4.1 Vulnerability and Measured Land of Households have almost inverse relationship. Households that have more measured land have less vulnerability and vise-versa. More specifically, Figure 4.1 shows that the less vulnerable (shows in panel 0), high vulnerable (shows in panel 1), and the total index group which is related to measured land. For the less vulnerable group (Panel 0), the more land the households have the sharper and less vulnerable the household is than the highly vulnerable group (panel 1). However, the highly vulnerable group of the households have a less decrement even if the land gets to increase. And The cumulative sum of both the less and highly vulnerable group (total) show an inverse relationship with the amount of land that the households have.

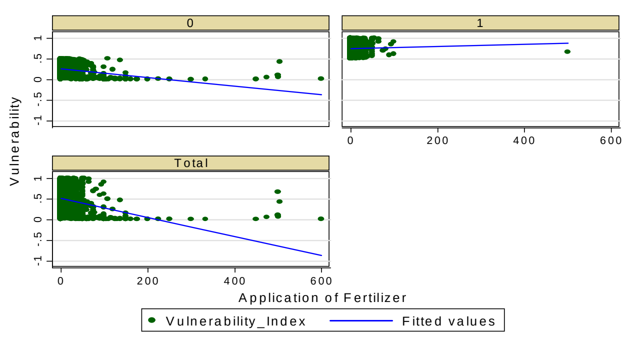

Figure 4.2: Vulnerability and Application of Fertilizer
Source: Own computation from ESS Data

The overall picture from figure 4.2 shows that vulnerability is higher among the low productive households: the low constitute 90% of the entire sample at the cutoff point of 6 quintals production, but about 52% of those who are highly vulnerable. On the other hand, the lower productive households are less likely to be vulnerable as they make up 42.8% of those who are less vulnerable.

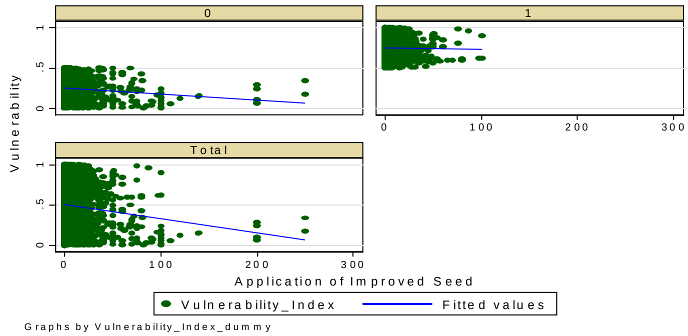

Figure 4.3: Vulnerability and Improved seed use

Source: Own computation from ESS Data

As can be observed, the scatter plot in figure 4.3 the relationship of vulnerability and application of improved seed is important. More specifically, Figure 4.3 indicates that the less vulnerable (shows in panel 0), high vulnerable (shows in panel 1), and the total index group which is related to improved seed . For the less vulnerable group (Panel 0), the more land the households have the sharper and less vulnerable the household is than the highly vulnerable group (panel 1). However, the highly vulnerable group of the households have a less decrement or almost horizontal even if the land gets to increase. And The cumulative sum of both the less and highly vulnerable group (total) show an inverse relationship with the improved seed that the households applied in their crop.

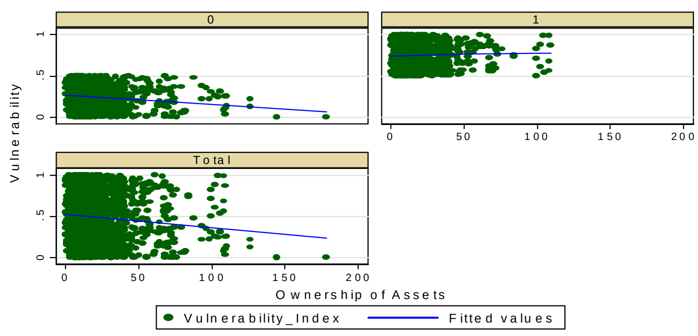

Figure 4.4: Vulnerability and Ownership of Assets

Source: Own computation from ESS Data

Figure 4.4 is a scatter plot of the value of household assets versus the vulnerability index. On the horizontal axis is the total number of assets possessed by households and on the vertical axis is the vulnerability index of various households in the group of lower and higher vulnerable. Generally, households with greater endowments of assets will tend to be less vulnerable. As shown in figure 4.4 indicates there is a clear negative relationship between ownership of assets and vulnerability with households becoming less vulnerable as the asset value rises. The number of oxen and year of schooling has a negative relationship with vulnerability (see Appendix E and H). But unexpectedly, the number of plot increase vulnerability to low production (Appendix G). However, the relationship of vulnerability with the household size is less clear, as illustrated in Appendices I.

Table 4.4: Results from Probit Model (Determinants of Vulnerability)

VARIABLES	Coefficient	Standard error	Marign.eff	Standard error
Total Fertilizer	-0.0226***	(0.00327)	-0.00859***	(0.00123)
Fertlizer squared	4.12e-05***	(7.03e-06)	1.57e-05***	(2.65e-06)
Improved seed	-0.0273	(0.0268)	-0.0104	(0.0102)
Improved seed squared	0.000209	(0.000451)	7.96e-05	(0.000171)
Pesticide	0.346**	(0.171)	0.132**	(0.0650)
Herbicide	-0.611***	(0.109)	-0.232***	(0.0412)
Fungicide	-0.858**	(0.426)	-0.326**	(0.162)
Hired Labor	-0.342***	(0.0574)	-0.130***	(0.0216)
Land certificate	0.156**	(0.0748)	0.0592**	(0.0284)
Number of Oxen	-0.484***	(0.0633)	-0.184***	(0.0240)
Number of Plots	0.690***	(0.0614)	0.262***	(0.0233)
Age of the household head	0.0161	(0.0180)	0.00612	(0.00684)
Household head Age Squared	-0.000228	(0.000165)	-8.68e-05	(6.28e-05)
Household Size	-12.09**	(4.920)	-4.598**	(1.871)
Household Size Squared	5.183**	(2.135)	1.971**	(0.812)
Years of schooling	-0.137***	(0.0407)	-0.0520***	(0.0155)
Proportion of Adult	-1.327***	(0.428)	-0.505***	(0.163)
Head Sex	0.0583	(0.108)	0.0222	(0.0413)
Constant	5.484***	(1.926)		
Observations	1,959			
Wald chi2(41)	439.77			
Prob > chi2	0.0000			

Key: *** p<0.01, ** p<0.05, * p<0.1 shows statistically significant at 1%, 5%, and 10% level respectively. Robust standard errors are in parentheses.

Table 4.4 presents the results of probit regression of the determinants of vulnerability. Overall, the model is a good fit as indicated by the Wald statistic. The application of total fertilizer decrease vulnerability but if it is used extensively it will increase vulnerability as value observed from the coefficient of fertilizer secured which is negative and significant. Conversely, improved seed increases vulnerability but if households used it extensively it will decrease vulnerability. Other technology indicators like fungicide and herbicide decrease households to be vulnerable in the future. However, pesticide increases vulnerability although it is insignificant.

The result strongly indicates that increased educational attainment of the household head, as well as each household member (aggregated b years of schooling), reduces vulnerability. Household size is negatively related to vulnerability, with each additional household member decrease the likelihood of being vulnerable by approximately 12.1%. Once more, having the land certificate is observed to be negatively associated with vulnerability. Households with more oxen are less likely to be vulnerable.

Households whose heads are illiterate are by far the most vulnerable groups and household heads who had up to primary level education are more vulnerable and poor as compared to secondary and higher-level education. Household Size Squared increases the probability of being vulnerable. Hired labor and the proportion of Adults in the household, on the other hand, reduce the likelihood of vulnerability.

Chapter 5

Conclusions and Implications

This study attempted to investigate the impact of agricultural technologies on land productivity in rural Ethiopia. The study used the three waves of Ethiopian Socio-economic survey (ESS) panel data of 5415 households collected in 2011/12, 2013/14, and 2015/16 by a collaborative effort of Central statistical Authority (CSA) and World Bank. To estimate the effect of the adaption and/or application of technologies on land productivity panel fixed effect model is estimated in three different specifications. The results indicated technologies such as fertilizer, improved seed, herbicide, and fungicide have a positive impact on land productivity. However, the pesticide has a negative impact although it is found to be insignificant. Other variables which include labor, crop rotation, and size of land owned by the household, and the livestock wealth (number of oxen), the health of the household have a positive and significant impact on land productivity.

The author also estimates quantile regression to see whether the same set of variables determine land productivity. The result indicates that technologies such as fertilizer, improved seed, and fungicide were positive and significant in determining land productivity. This implies that the adaption of these technologies improves land productivity. In addition, labor, health, and crop rotation, and household size (at lower quantile) have a positive and significant impact on Land productivity. However, the number of crops and number of plots are found negative and significant determinants of Land productivity. These findings from both panel fixed model and quantile regression have huge implications for land productivity targeting. Land productivity can be improved by high farm technology adoption. The policy package might also include crop rotation, education, health reform, and labor intensification.

The study also addresses vulnerability to low land productivity, which is defined to be the probability that a household will have a lower crop yield or shock in the future. A range of technology adoption measures such as fertilizer, improved seed, pesticide, fungicide, and herbicide use, and also household and community characteristics, were considered in constructing a measure of vulnerability more specifically developed using three stages least square estimation. After developing a vulnerability index we estimate a probit model by dividing a vulnerability index into 0 (vulnerability index below 0.5) and 1 (Index above 0.5). the result from the probit model shows that vulnerability is higher among the bottom households (low productive) those who produce less than six quintals as compared to the higher household (higher productivity)-those who produce above six quintals. Moreover, Households who having more oxen, land ownership right/certificates, and who employee labor on the farm are less likely to be vulnerable. Households whose heads are illiterate are by far the most vulnerable groups and household heads who had up to primary level education are more vulnerable and poor as compared to secondary and higher-level education. Household Size Squared increases the probability of being vulnerable. On the other hand, high proportions of Adults in the household reduce the likelihood of vulnerability.

Finally, the adaption of improved technologies benefits both lower as well as highly productive households. Thus, by adopting agricultural technologies like fertilizer, improved seed, herbicide, and fungicide there is a synergy to increase crop yield. An important policy implication of this is that the current agricultural extension program and safety net program could focus on the promotion of and support for the adoption of these improved technologies to rescue rural farmers from vulnerability. There is a discrepancy between lower productive and higher productive in terms of vulnerability when they adopt a given technology. Therefore, policymakers should take into account this heterogeneity to unleash the full acquired benefit of the technology.

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Appendix

Appendix A: Description of Variables and summary statistics

VARIABLES	Description	Mean	SD	min	max
Land productivity	Crop cut production measured in quintals	2.499	8.898	0	511.8
Fertilizer	Total fertilizer application, in kg	7.579	26.21	0	600
Improved seed	Amount of improved seed application, in kg	4.218	13.59	0	250
Pesticide	1=If the household use Pesticide on crop	0.026	0.161	0	1
Herbicide	1=If the household use Herbicide on crop	0.111	0.314	0	1
Fungicide	1=If the household use Fungicide on crop	0.006	0.081	0	1
Measured Land	Plot size measured using GPS, in hectare	0.191	0.430	.0002	11.53
Compost	1=If the household apply compost on crop	0.050	0.219	0	1
Family Labor	Total household labor used on plot, person days	11.69	14.72	0	184.4
Hired Labor	Total hired labor used on plot, person days	4.286	73.85	0	2,479
Shared Labor	Total labor used from other households	1.650	6.741	0	168
Land Certificate	1 = if the household has land ownership right	0.618	0.486	0	1
ADL-Index	Activity Daily living Index	23.77	1.172	0	24
Total Oxen	Total number of Oxen	0.547	1.222	0	14
Number of plots	Number of plots	2.449	2.629	1	24
Number of crops	Number of crops	1.119	0.415	1	5
Household size	Household size	5.747	2.199	1	16
Head Sex	Head Sex	0.865	0.342	0	1
Prop of Adult in hh	Proportion of Adult in a household	0.837	0.093	0	1.1
Household Age	Age of the household head	49.00	14.31	18	97.17
Year of schooling	Year of schooling	2.018	5.461	0	96
Read Write Dummy	1=If the household head read and write	0.440	0.496	0	1
Irrigation Dummy	1=use irrigation	0.022	0.147	0	1
Plot Slope Dummy	1=sloppy and 0 otherwise)	0.106	0.308	0	1
Soil Quality Dummy	1=if the soil quality is good	0.209	0.407	0	1
PSNP Dummy	1=if participated in Productive Safety Net Programme	0.045	0.207	0	1
Crop Rotation	1 = if crop rotation is applied on the land	0.883	0.322	0	1
Extension Dummy	1 = if received government extension services	0.492	0.500	0	1
	Observations=5415 & Number of Cluster=1739				

Appendix B: Panel Fixed Effect Model Estimation of Land Productivity for Male and Female Headed Households

	Dependent Variable: Log Land Productivity					
	Male			Female		
VARIABLES	1	2	3	1	2	3
Ln Fertilizer	0.114*** (0.0114)	0.113*** (0.0114)	0.115*** (0.0114)	0.144*** (0.0353)	0.144*** (0.0348)	0.154*** (0.0371)
Ln Improved Seed	0.138*** (0.0181)	0.135*** (0.0183)	0.134*** (0.0184)	0.106 (0.0703)	0.103 (0.0697)	0.111 (0.0713)
Pesticide	−0.130 (0.0934)	−0.133 (0.0931)	−0.130 (0.0935)	0.0521 (0.111)	0.0283 (0.113)	0.0223) (0.109)
Herbicide	0.0687 (0.0454)	0.0644 (0.0455)	0.0628 (0.0456)	−0.0104 (0.0837)	−0.0309 (0.0824)	−0.0361 (0.0833)
Fungicide	0.305*** (0.149)	0.306** (0.152)	0.302** (0.153)	0.899*** (0.290)	0.902*** (0.253)	0.960*** (0.218)
Compost	0.0355 (0.0512)	0.0302 (0.0514)	0.0334 (0.0518)	−0.136 (0.158)	−0.134 (0.151)	−0.115 (0.156)
Ln Household Labor	0.159*** (0.0150)	0.158*** (0.0155)	0.160*** (0.0155)	0.118*** (0.0344)	0.115*** (0.0340)	0.122*** (0.0352)
Ln Hired Labor	0.137*** (0.0196)	0.134*** (0.0200)	0.132*** (0.0200)	0.109* (0.0565)	0.112* (0.0572)	0.117** (0.0573)
Ln Shared labor	0.112*** (0.0202)	0.103*** (0.0203)	0.103*** (0.0203)	0.163*** (0.0422)	0.151*** (0.0411)	0.152*** (0.0405)
Land certificate	−0.124** (0.0483)	−0.128*** (0.0484)	−0.123*** (0.0477)	0.112 (0.177)	0.132 (0.171)	0.131 (0.164)
Ln Oxen	0.0756 (0.0561)	0.0740 (0.0559)	0.0914* (0.0552)	0.159 (0.117)	0.182 (0.119)	0.182 (0.121)
Ln ADL_index	0.0772 (0.0592)	0.0815 (0.0601)	0.0668 (0.0514)	7.458*** (1.415)	7.261*** (1.598)	6.972*** (1.579)
Ln Number of Plots		−0.0835*** (0.0235)	−0.0856*** (0.0238)		−0.141** (0.0644)	−0.135** (0.0661)
Ln Head Age		0.385* (0.228)	0.356 (0.224)		−0.609 (0.466)	−0.507 (0.493)
Ln Household Size		−0.200** (0.101)	−0.211** (0.103)		−0.0275 (0.198)	−0.0292 (0.203)
Ln Number of crops		0.104 (0.0888)	0.100 (0.0884)		0.519** (0.225)	0.521** (0.239)
Irrigation Dummy			0.0139 (0.106)			0.288 (0.539)
Plot Slope Dummy			0.0475 (0.0401)			0.149 (0.154)
Soil Quality Dummy			0.0383 (0.0352)			−0.0327 (0.0931)
PSNP Dummy			0.0157 (0.0914)			−0.106 (0.143)
Crop Rotation Dummy			0.127* (0.0719)			0.104 (0.179)
Extension Dummy			0.0503 (0.0428)			0.00655 (0.0864)
Read Write Dummy			−0.00357 (0.0551)			0.252 (0.170)
Constant	0.118 (0.201)	−0.967 (0.956)	−1.051 (0.953)			−20.09*** (5.855)
Observations	4,685	4,685	4,685	730	730	730
Number of cluster	1,472	1,472	1,472	269	269	269
R-squared	0.281	0.287	0.289	0.380	0.394	0.401
Household,Year & Crop FE	Yes	Yes	Yes	Yes	Yes	Yes

*Key: *** p<0.01, ** p<0.05, * p<0.1 shows statistically significant at 1%, 5%, and 10% level respectively. Robust standard errors are in parentheses.*

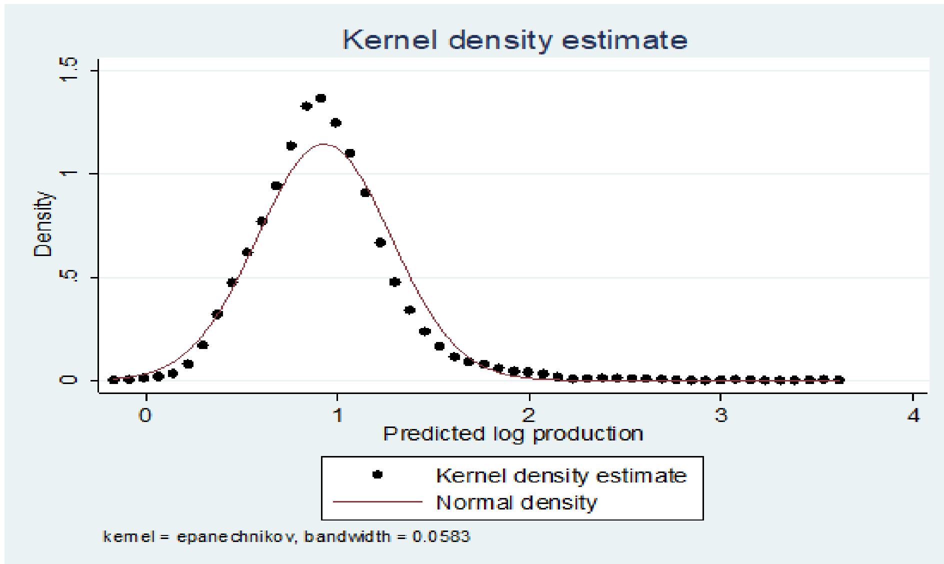
Source: Author Computation from Ethiopian Socio-economic Survey (ESS)

Appendix C: Results from Three Stages Feasible Generalized Least Squares Estimation

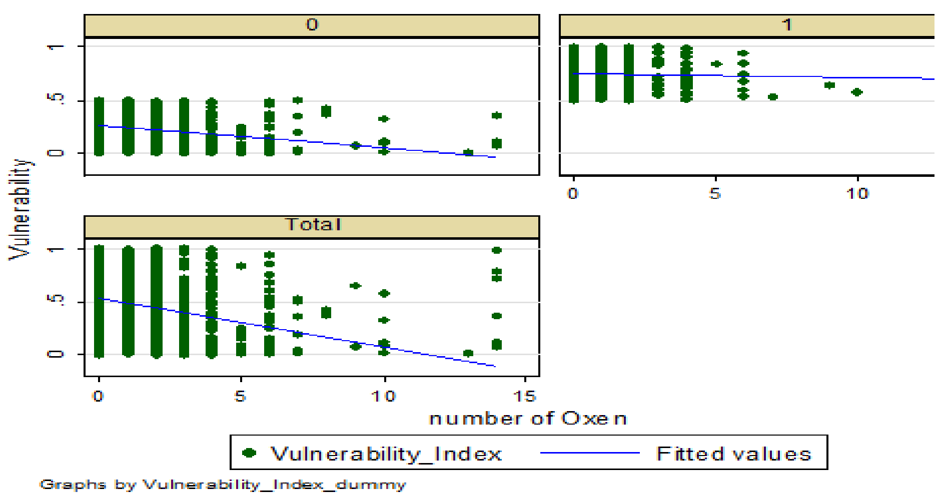
VARIABLES	Stage 1 Log Production	Stage 2 Error_square	Stage 3 Log Production
Total fertilizer	0.00813*** (0.00102)	−0.00217** (0.000942)	0.00813*** (0.000)
Fertlizer squared	$-1.49e-05$*** ($2.25e{-}06$)	$4.68e-06$** ($2.08e{-}06$)	$-1.49e-05$*** (0.000)
Improved seed	0.00860 (0.000102)	0.0119 ($9.45e{-}05$)	0.00860*** ($3.31e{-}10$)
Improved seed squared	$-9.45e-05$ (0.0406)	−0.000170* (0.0407)	$-9.45e-05$*** (0.000)
Pesticide	−0.195** (0.0830)	−0.0242 (0.0767)	−0.195*** ($3.31e{-}09$)
Herbicide	0.146*** (0.153)	0.142*** (0.141)	0.146*** ($6.09e{-}09$)
Fungicide	0.480*** (0.153)	0.0131 (0.141)	0.480*** ($6.09e{-}09$)
Hired Labor	0.151*** (0.0183)	0.0330** (0.0158)	0.151*** ($6.80e{-}10$)
Land certificate	−0.0542 (0.0333)	−0.0149 (0.0307)	−0.0542*** ($1.33e{-}09$)
Number of Oxen	0.246*** (0.0275)	0.0836*** (0.0254)	0.246*** ($1.09e{-}09$)
Number of Plots	−0.256*** (0.0508)	−0.119*** (0.0507)	−0.256*** (0.0502)
Number of Plots	−0.256*** (0.0277)	−0.119*** (0.0256)	−0.256*** ($1.10e{-}09$)
Age of the household head	−0.00120 (0.00823)	0.00210 (0.00759)	−0.00120*** ($3.27e{-}10$)
Household head Age Squared	$2.28e-05$ ($7.52e{-}05$)	$1.53e-06$ ($6.94e{-}05$)	$2.28e-05$*** (0.000)
Household Size	1.925 (2.211)	4.344** (2.041)	1.925*** ($8.80e{-}08$)
Household Size Squared	−0.836 (0.960)	−1.876** (0.886)	−0.836*** ($3.82e{-}08$)
Years of schooling	0.0221 (0.0184)	0.0423** (0.0170)	0.0221*** ($7.33e{-}10$)
Proportion of Adult	0.570*** (0.198)	0.172 (0.183)	0.570*** ($7.89e{-}09$)
Head Sex	−0.00297 (0.0495)	0.0211 (0.0457)	−0.00297*** ($1.97e{-}09$)
Constant	−0.309 (0.870)	−1.486* (0.803)	−0.309*** ($3.46e{-}08$)
Observations	1,963	1,963	1,963

Key: *** p<0.01, ** p<0.05, * p<0.1 shows statistically significant at 1%, 5%, and 10% level respectively. Standard errors are in parentheses.

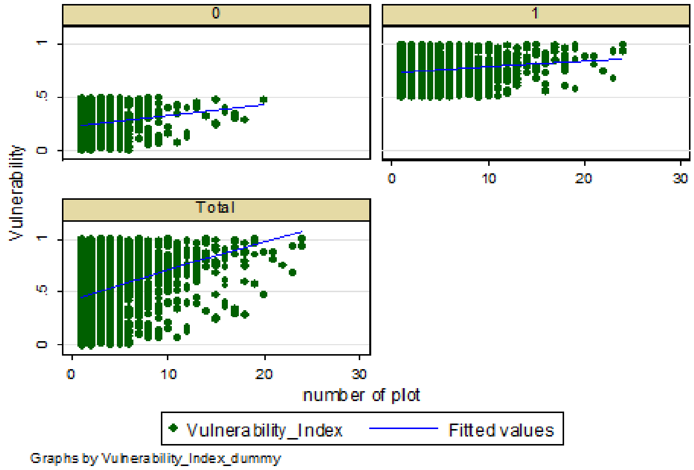
Appendix D: Kernel Density of Expected log Production



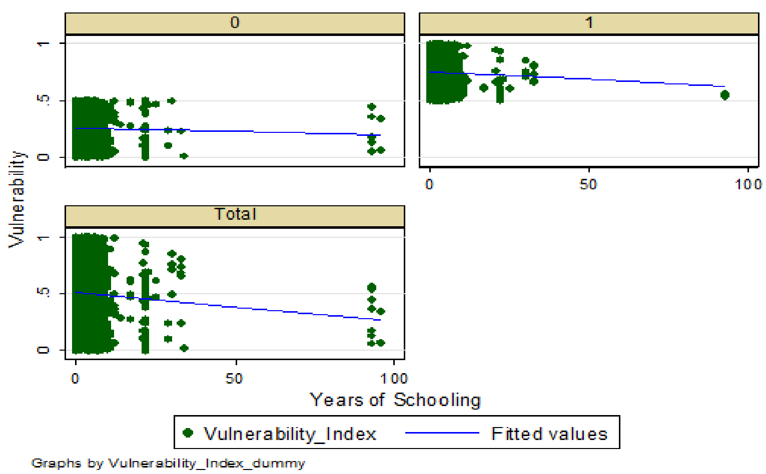
Appendix E: Vulnerability and Number of Oxen



Appendix G: Vulnerability and Numbers of plot



Appendix H: Vulnerability and Year of Schooling



Appendix I: Vulnerability and Household Size