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The Impact of Agricultural Innovations on Poverty, Vulnerability and Resilience to Food Insecurity of Smallholders in Ethiopia

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To Dessalegn Biru and Mulu Beyene

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Executive Summary

Ethiopia has adopted agriculture centered growth strategies over the last three decades that give more emphasis on improving agricultural production and productivity with the ultimate goal to transform the country's economy. The strategies have mainly aimed at improving smallholder agriculture through introducing improved technologies intended to boost agricultural production and thus alleviate poverty and food insecurity. Although agriculture centered growth strategies contributed to sustained growth in the country over the last two decades, the benefits of growth have not been evenly distributed with observed rising income inequality and a still significant proportion of smallholders remaining under the poverty line. Similarly, despite considerable yield progress over the last three decades due to the introduction of improved inputs Ethiopian farmers' yield gap compared with other developing countries is quite high. Moreover, the frequent occurrences of shocks such as drought and flooding adversely affect smallholders substantially and thereby exacerbate the existing poverty and food insecurity problems in the country.

This thesis applied different econometric techniques to analyze the impact of the adoption of multiple agricultural technologies on crop yield, poverty, vulnerability, and resilience to food insecurity in Ethiopia. The study uses four rounds of household level panel data collected between 2012 and 2019 to assess the link between the adoption of the different combinations of five productivity-enhancing technologies: chemical fertilizer, improved seed, pesticide, and soil and water conservation practices: terracing and contour ploughing on consumption, poverty, vulnerability, and yields of smallholders. To solve the endogeneity problem in the regression models, we applied two-stage multinomial endogenous switching regression model combined with the Mundlak approach. Additionally, the thesis examines the role of the adoption of chemical fertilizer and improved seeds on household resilience to food insecurity amid the occurrence of adverse shocks. The findings are presented in three chapters of the cumulative thesis (Chapters two to four).

Chapter two analyses the effect of productivity enhancing technologies and soil and water conservation measures and their possible combinations on consumption, poverty, and vulnerability to poverty. Per capita consumption expenditure for food and other essential non-food items, such as clothing and footwear, is used as a proxy variable to measure poverty. Using the national poverty line in 2011 prices, sample households are grouped into poor and non-poor households and the movement of sample households in and out of poverty between 2012 and 2016 is analyzed using a poverty transition matrix. By employing the ordered logit model, the

study additionally examined the dynamics of poverty and vulnerability as well as their drivers. The results show that the adoption of the different combinations of agricultural technology sets including single technology adoption has considerable impacts on consumption expenditure and the greatest impact is attained when farmers combine multiple complementary inputs. Similarly, we find that the likelihood of households remaining poor or vulnerable decreased with adoption. In addition, the study revealed that poorer households are the least adopters of the technology combinations considered in the study, thereby being the least to benefit from adoption. We, therefore, conclude that the adoption of multiple complementary technologies has substantial dynamic benefits that improve the poverty and vulnerability status of households, 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.

Chapter three assesses the impacts of multiple technology adoption on the yield of Ethiopia's four staple crops, namely teff, wheat, maize and barley. Regarding the empirical estimation, we specified yield equations for each of the four crops and five to six possible input combinations that are included in the analysis indicating the presence of slope effect of technology choice other than the intercept of the outcome equations. The findings suggest that the application of two or more complementary inputs is considerably linked with higher maize, teff, barley, and wheat yield. Specifically, barley yield is highest for farmers who have adopted a combination of at least three of the technologies. Maize producers are the largest beneficiaries of the technologies. The impact of the technology choice sets tends to have an inconclusive effect on wheat and teff yields. However, a significant yield gap in all of the four crops was observed. Socio-economic characteristics of the household head such as age and gender as well as the household's access to infrastructure and spatial characteristics of the household are other important determinants of crop yield. The implications are that more publicly funded efforts could be worthwhile for easing adoption constraints, which would in turn help smallholders to increase their crop yields that indirectly improve their livelihood.

Chapter four aims to identify the determinants of household resilience to food insecurity which is the household's ability to absorb or cope with the negative effects of shocks and bounce back to at least their initial livelihood status and assess its role on future household food security when hit by adverse shocks. Furthermore, the study analyzes the role of single or joint adoption of chemical fertilizer and improved seed on household food security. The household food security indicators used in the analysis are dietary diversity and per capita food consumption

and uses data from the last three waves out of our four survey rounds. In terms of empirical estimation, the household resilience capacity index is estimated by combining factor analysis and structural equation modeling. Then different regression models are executed to assess the causal link between technology adoption and resilience capacity and household food security indicators in the face of adverse shocks. Our findings reveal that the most important pillars contributing to the building of household resilience capacity are assets followed by access to basic services. We find that the initial level of the household resilience score is significantly and positively associated with future household food security status. Moreover, the results reveal that the adoption of chemical fertilizer and improved seed is significantly and positively associated with household resilience capacity index, dietary diversity, and food consumption over time. Shocks such as drought appear to be significant contributors to the loss of household food security. Overall, it is revealed that the adoption of improved inputs significantly and positively increases household food security. However, the results show no evidence that supports the current level of adoption that helps households to shield themselves from the adverse effects of shocks.

Finally, this study gives insights on examining the impacts and impact pathways of adoption of improved technologies on smallholder welfare which guide decision-makers for intervention as well as pave a way for future research that contributes to the fight against rural poverty and food insecurity. This thesis also concludes that public intervention in terms of investment in providing improved agricultural practices is crucial in improving rural livelihood, but it has to be inclusive and provide opportunities for the poor and vulnerable.

Zusammenfassung

Äthiopien hat in den letzten drei Jahrzehnten agrarzentrierte Wachstumsstrategien verfolgt, die den Schwerpunkt auf die Verbesserung der landwirtschaftlichen Produktion und Produktivität legen, um die Wirtschaft des Landes zu transformieren. Die Strategien zielten hauptsächlich darauf ab, die kleinbäuerliche Landwirtschaft durch die Einführung verbesserter Technologien zu verbessern, um die landwirtschaftliche Produktion zu steigern und damit Armut und Ernährungsunsicherheit zu lindern. Obwohl die auf die Landwirtschaft ausgerichteten Wachstumsstrategien in den letzten zwei Jahrzehnten zu einem nachhaltigen Wachstum im Land beigetragen haben, war diesesWachstum nicht gleichmäßig verteilt. Es wurde eine steigende Einkommensungleichheit beobachtet und ein immer noch erheblicher Anteil der Kleinbauern lebt unterhalb der Armutsgrenze. Ebenso ist die Ertragslücke der äthiopischen Bauern im Vergleich zu anderen Entwicklungsländern trotz der Einführung verbesserter Betriebsmittel recht hoch. Darüber hinaus beeinträchtigen häufige Schocks wie Dürre und Überschwemmungen insbesondere die Kleinbauern erheblich und verschärfen dadurch die bestehenden Probleme der Armut und Ernährungsunsicherheit im Land.

In dieser Arbeit wurden verschiedene ökonometrische Methoden angewandt, um die Auswirkungen der Einführung mehrerer landwirtschaftlicher Technologien auf Ernteerträge, Armut, Anfälligkeit und Widerstandsfähigkeit gegenüber Ernährungsunsicherheit in Äthiopien zu analysieren. Die Studie verwendet vier Runden von Paneldaten auf Haushaltsebene. Diese wurden zwischen 2012 und 2019 wurden, um den Zusammenhang zwischen der Einführung verschiedener Kombinationen von fünf produktivitätssteigernden Technologien - chemischer Dünger, verbessertes Saatgut, Pestizide sowie Boden- und Wasserschutzpraktiken wie Terrassierung und Konturpflügen - auf Konsum, Armut, Vulnerabilität gegenüber Armutsgefährdung und Erträgen von Kleinbauern zu untersuchen. Um das Endogenitätsproblem in den Regressionsmodellen zu lösen, haben wir ein zweistufiges multinomiales endogenes Switching-Regressionsmodell in Kombination mit dem Mundlak-Ansatz verwendet. Zusätzlich untersucht die Arbeit die Rolle der Adoption von chemischem dünger und verbessertem Saatgut auf die Resilienz der Haushalte gegenüber Ernährungsunsicherheit. Die Ergebnisse werden in drei Kapiteln einer kumulativen Dissertation vorgestellt (Kapitel zwei bis vier).

In Kapitel zwei werden die Auswirkungen von produktivitätssteigernden Technologien und Boden- und Wasserschutzmaßnahmen sowie deren mögliche Kombinationen auf Konsum, Armut und Armutsgefährdung analysiert. Die Pro-Kopf-Konsumausgaben für Nahrungsmittel

und andere wichtige Güter des täglichen Bedarfs, wie Kleidung und Schuhe, werden als Proxy-Variable zur Messung von Armut verwendet. Unter Verwendung der nationalen Armutsgrenze mit Preisen von 2011 werden die Stichprobenhaushalte in arme und nicht arme Haushalte eingeteilt. Die Bewegung der Stichprobenhaushalte in und aus der Armut zwischen 2012 und 2016 wird mithilfe einer Armutsübergangsmatrix analysiert. Durch den Einsatz eines geordneten Logit-Modells wurden in der Studie zusätzlich die Dynamik von Armut und Armutsgefährdung sowie deren Treiber untersucht. Die Ergebnisse zeigen, dass die Adoption verschiedener Kombinationen von landwirtschaftlichen Technologien, sowie die Adoption von einzelnen Technologien, erhebliche Auswirkungen auf die Konsumausgaben haben. Die größte Auswirkung wird erreicht , wenn Landwirte mehrere komplementäre Betriebsmittel kombinieren. Ebenso stellen wir fest, dass die Wahrscheinlichkeit, dass Haushalte arm oder armutsgefährdet bleiben, mit der Adoption von Technologien abnimmt. Darüber hinaus ergab die Studie, dass ärmere Haushalte die wenigsten der in der Studie betrachteten Technologiekombinationen nutzen und somit am wenigsten davon profitieren. Wir kommen daher zu der Schlussfolgerung, dass die Anwendung mehrerer komplementärer Technologien erhebliche Vorteile hat, die den Armutsstatus und Armutsgefährdungsstatus der Haushalte verbessern Angesichts der beobachteten niedrigen Adoptionsraten empfehlen wir, dass viel mehr Interventionen gerechtfertigt sind. Mit einem besonderen Fokus auf ärmere und armutsgefährdete Haushalte sollten diese sicherzustellen, dass Kleinbauern Unterstützung erhalten, um ihre Betriebsmittel- und Technologienutzung zu verbessern.

In Kapitel drei werden die Auswirkungen des Einsatzes mehrerer Technologien auf den Ertrag der vier äthiopischen Grundnahrungsmittel Teff, Weizen, Mais und Gerste untersucht. Für die empirische Schätzung haben wir Ertragsgleichungen für jede der vier Kulturen und fünf bis sechs mögliche Betriebsmittel-Kombinationen spezifiziert, die in die Analyse einfließen und auf das Vorhandensein eines Neigungseffekts der Technologiewahl neben dem Achsenabschnitt der Ergebnisgleichungen hinweisen. Die Ergebnisse deuten darauf hin, dass die Anwendung von zwei oder mehr komplementären Inputs signifikant mit höheren Mais-, Teff-, Gersten- und Weizenerträgen zusammenhängt. Insbesondere der Gerstenertrag ist bei Landwirten am höchsten, die eine Kombination von mindestens drei der Technologien eingesetzt haben. Maisproduzenten sind die größten Nutznießer der Technologien. Die Auswirkung der Technologiekombinationen auf die Weizen- und Tefferträge ist tendenziell nicht eindeutig. Es wurde jedoch ein signifikanter Ertragsunterschied bei allen vier Feldfrüchten beobachtet. Sozioökonomische Merkmale des Haushaltsvorstands wie Alter und Geschlecht sowie der Zugang des Haushalts zur Infrastruktur und räumliche Merkmale des Haushalts sind weitere wichtige Determinanten des Ernteertrags. Die Implikationen sind, dass mehr öffentlich finanzierte Anstrengungen lohnenswert sein könnten, um Adoptionsbeschränkungen abzubauen. Dies würde den Kleinbauern helfen, ihre Ernteerträge zu steigern, was indirekt ihren Lebensunterhalt verbessern würde.

Kapitel vier zielt darauf ab, die Determinanten der Resilienz der Haushalte gegenüber Ernährungsunsicherheit zu identifizieren, d.h. die Fähigkeit der Haushalte, die negativen Auswirkungen von Schocks zu absorbieren oder zu bewältigen und zu ihrer normalen Situation zurückzukehren, und ihre Rolle für die zukünftige Ernährungssicherheit der Haushalte zu bewerten, wenn sie von widrigen Schocks betroffen sind. Darüber hinaus analysiert die Studie die Rolle der alleinigen oder gemeinsamen Anwendung von chemischem Dünger und verbessertem Saatgut auf die Ernährungssicherheit der Haushalte. Die Indikatoren für die Ernährungssicherheit der Haushalte, die in der Analyse verwendet werden, sind die Ernährungsvielfalt und der Pro-Kopf-Verbrauch an Nahrungsmitteln. Es werden Daten aus den letzten drei Runden der vier Erhebungsrunden verwendet. Was die empirische Schätzung betrifft, so wird ein Index für die Resilienzfähigkeit der Haushalte durch eine Kombination von Faktorenanalyse und Strukturgleichungsmodellierung geschätzt. Anschließend werden verschiedene Regressionsmodelle durchgeführt, um den kausalen Zusammenhang zwischen Technologieadoption und Resilienzkapazität und den Indikatoren der Ernährungssicherheit von Haushalten angesichts widriger Schocks zu bewerten. Unsere Ergebnisse zeigen, dass die wichtigsten Säulen, die zum Aufbau von Resilienzkapazitäten von Haushalten beitragen, Vermögenswerte sind, gefolgt vom Zugang zu Basisdienstleistungen. Wir stellen fest, dass die Resilienzfähigkeit der Haushalte signifikant und positiv mit dem zukünftigen Status der Ernährungssicherheit der Haushalte verbunden ist. Darüber hinaus zeigen die Ergebnisse, dass der Einsatz von chemischem Dünger und verbessertem Saatgut signifikant und positiv mit dem Resilienzindex der Haushalte, der Ernährungsvielfalt und dem Nahrungsmittelkonsum im Zeitverlauf zusammenhängt. Schocks wie Dürre scheinen signifikant zum Verlust der Ernährungssicherheit der Haushalte beizutragen. Insgesamt zeigt sich, dass der Einsatz von verbesserten Betriebsmitteln die Ernährungssicherheit der Haushalte signifikant und positiv erhöht. Es wird jedoch auch beobachtet, dass die Haushalte nicht in der Lage sind, sich vor den negativen Auswirkungen von Schocks zu schützen.

Abschließend gibt diese Studie Einblicke in die Untersuchung der Auswirkungen und Wirkungspfade der Einführung verbesserter Technologien auf das Wohlergehen von Kleinbauern, die Entscheidungsträgern eine Anleitung für Interventionen geben und einen Weg für zukünftige Forschung ebnen, die zum Kampf gegen ländliche Armut und Ernährungsunsicherheit beiträgt. Diese Arbeit kommt auch zu der Schlussfolgerung , dass öffentliche Interventionen in Form von Investitionen in die Bereitstellung verbesserter landwirtschaftlicher Praktiken von entscheidender Bedeutung für die Verbesserung der ländlichen Lebensbedingungen sind. Jedoch müssen diese inklusiv sein und Möglichkeiten für arme und armutsgefährdete Haushalte bieten.

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List of Acronyms

AB	Arrelano Bond
ADLI	Agricultural Development Lead Industrialization
ATA	Agricultural Transformation Agency
ATT	Average Treatment Effect on the Treated
CAPI	Computer Assisted Personal Interviewing
DAAD	Deutsche Akademischer Austausch Dienst
DFG	Deutsche Forschungsgemeinschaft
DPD	Dynamic Panel Data
ESMNL	Endogenous Switching Multinomial Logit
ETB	Ethiopian Birr
FA	Factor Analysis
FAO	Food and Agriculture Organization
GMM	Generalized Method of Momen
GDP	Gross Domestic Product
GTP	Growth and Transformation Plan
HDD	Household Dietary Diversity
IFPRI	International Food Policy Research Institute
OLS	Ordinary Least Square
MIMIC	Multiple Indicators and Multiple Causes
MNL	Multinomial Logit
MoFED	Ministry of Finance and Economic Development
RCI	Resilience Capacity Index
RIMA	Resilience Index Measurement and Analysis
RMTWG	Resilience Measurement Technical Working Group
SEM	Structural Equation Modeling
SNNPR	Southern Nations Nationalities and Peoples Region
TLU	Tropical Livestock Unit
UNFCCC	United Nations Framework Convention on Climate Change
VER	Vulnerability as uninsured exposure to risk (and
VEU	Vulnerability as Low Expected Utility
VEP	Vulnerability as Expected poverty

Chapter One

1. Introduction

This chapter presents general information on the links between technology adoption, shocks, and household welfare outcomes represented by consumption expenditure, poverty, vulnerability, yield, and resilience of smallholders in Ethiopia. Following the general introduction, the chapter then presents a basic conceptual framework on the link between technology adoption, shocks, and welfare outcomes. Following the conceptual framework, the chapter introduces the main research questions addressed in this thesis and, finally, an outline on the structure of the remaining chapters.

1.1 General Introduction

Agriculture continues to be the main source of employment, livelihood, and income for more than 80% of the population in rural areas in developing countries. Of this percentage, the overwhelming majority are smallholders making up to 90% of the farming population. Smallholders predominantly practice rainfed agriculture with limited use of improved agricultural practices, using family labour for production. As a result, rural households' livelihood is characterized by widespread poverty and food insecurity in many developing countries. Particularly, Sub-Saharan Africa (SSA) has the highest number of people living in extreme poverty, comprising 413.3 million people in 2015 (Beegle et al., 2016). The number has grown substantially since the 1990s and about 88% of the world's poorest are expected to live in Africa by 2030 (World Bank, 2015).

Similar to other SSA countries, the majority of Ethiopia's population is heavily dependent on subsistence rain-fed agriculture, with about 80% of the population living in rural areas. The agricultural sector takes the highest share of the country's national economy, accounting for about 43% of GDP, 90% of exports, and 96% of rural employment (MoFED, 2010). Smallholder farming dominates the agricultural sector in Ethiopia which accounts for more than 90% of the national cultivated area and provides more than 95% of the total agricultural output of the country. Despite their contributions to food security and the national economy of the country, farm households living in rural areas are faced with severe poverty and food insecurity which are even more pervasive than in urban areas (MoFED, 2008).

Despite sustained growth in agricultural production over the last few years, poverty in rural areas is still severe and more pervasive than in urban areas (MoFED, 2008). About 33% of the rural population lives below the national poverty line and an additional 14% of non-poor households are estimated to be vulnerable to falling into poverty (World Bank, 2015). While urban headcount poverty declined from 36.9% in 2000 to 14.8 % in 2016; rural poverty only declined from 45.4% to 25.6% in the same period. The most important factors blamed for the widespread poverty and food insecurity in SSA and specifically in Ethiopia are smallholders' reliance on rain-fed subsistence agriculture with no irrigation and limited use of improved technologies. Likewise, in Ethiopia rural households are not only prone to but also are vulnerable to adverse shocks due to negligible level of absorptive capacity or limited coping mechanisms that are used against the negative effects of shocks. For instance, Dercon (2004) reported that even non-poor households are vulnerable to poverty mainly because of their frequent exposure to various types of shocks as well as lack of coping mechanisms.

Teff, wheat, maize, sorghum, and barley are the five major cereal crops that are the core of Ethiopia’s agriculture and food economy, accounting for about three-fourths of the total area cultivated, 29 percent of agricultural gross domestic product (GDP) in 2005/06 (14 percent of total GDP), and 64 percent of calories consumed (calculated using FAO, various years). In SSA countries including Ethiopia, there has been substantial growth in cereal yields and production since 2000, but still smallholder yields in Ethiopia are low by international standards where only 20 percent of rainfed cereal yield potential is achieved (Atlas, 2021). Among others, limited adoption and recurring weather-related shocks are blamed to be the primary cause of the yield gap in the country (Abebe and Sewnet, 2014; Asfaw et al., 2011; Doss and Morris, 2000; Misiko and Ramisch, 2007; Pender et al., 2006).

In response to the aforementioned livelihood challenges, the Ethiopian government has initiated development programs, such as the Agricultural Development Lead Industrialization (ADLI) and Growth and Transformation Plans I and II (GTP I and GTP II), at different times with a special emphasis on improving agricultural productivity in the country (Howard et al., 2003; MoFED, 2010; MoFED, 2003). The strategies mainly concentrate on strengthening the interdependence between agriculture and industry by increasing the productivity of smallholder farmers through improved agronomic practices, research & extension, technology transfer, and rural infrastructure. To comply with the objective, research institutes in the country have been releasing several improved agricultural technologies in crops, livestock, and natural resource management practices over the last three decades. Evidence from studies conducted in selected areas of the country shows that a relatively significant proportion of farmers adopted improved technologies and practices (Doss et al., 2003; Mandefro et al., 2002; Tadesse and Degu, 2002).

However, unlike most of the developing world which showed a steady increase in output per capita over the last three decades, Ethiopia's per capita output has been stagnant during this period. Moreover, rural poverty and food insecurity are still pervasive in the country suggesting that the potential benefits of agricultural technology adoption are minimal.

In developing countries, particularly in SSA, several studies have been conducted to assess the impact of policies and programs on the welfare of rural households with particular emphasis on poverty and food security of rural households. And the results of these studies show that investments in public research and development (R&D), extension, education, and their links with one another have elicited high returns and pro-poor growth (World Bank, 2007a). Using the principal component analysis method with a cross-section data Mendola (2007), Nabasirye, Kiiza and Omiat (2012) and Becerril and Abdulai (2009) and also a similar impact analysis by Yao et al. (2015), Asfaw et al. (2012), and Gemeda et al. (2001) also found a positive impact of agricultural technology adoption in ending poverty and food insecurity. However, the majority of the studies examined the adoption and impacts of agricultural technology by presenting the decision to adopt as a single technology adoption choice. Thus, the evidence on the role of multiple technology adoption in reducing poverty and vulnerability or improving yield or resilience to food security, unfortunately, is sparse. Yet, the impacts of any agricultural technology arise from the use of multiple complementary and interrelated practices at the farm level. A single technology cannot reach its full potential unless complementary productivity-enhancing, as well as interrelated soil and water conservation measures, are also implemented. Using plot-level data, a study by Kassie et al. (2018) shows the maximum maize yield gain was achieved for farmers who combined fertilizer, improved maize seed, and legume. Incomplete adoption of technology packages or mismanagement is reported as an important factor for the stagnant yield among smallholders (Feder et al., 1985; Kassie et al., 2015). Moreover, the adoption of technologies in Ethiopia and elsewhere has uneven benefits among the different groups of households. The poor and vulnerable households are mostly the least to benefit from the impacts of new agricultural practices. To fully understand the direct and indirect dynamic impact of adoption on welfare as well as its role in absorbing the adverse effects of shocks; it is important to gain a more complete picture of adoption and links with the different welfare indicators. The use of rich panel data enables us to capture the impacts of technologies on welfare over time as well as capture the movement of households in and out of poverty over time (i.e. vulnerability to poverty).

In terms of resilience to food insecurity, smallholders in Ethiopia have limited or no possibilities to externalize or cope with the negative effect of shocks with insurance coverage. Rural households lack resource endowments such as skilled labor, land, improved inputs as well as productive assets such as oxen to cope with the adverse effects of shocks (Bogale et al., 2005; Borko, 2017; Eyasu, 2020). The impacts of shocks may considerably vary depending on the household’s livelihood diversification strategies, the extent of technology adoption, resilience capacity as well as yield potential. Thus, evaluating the role of improved inputs in building the resilience capacity as well as their role as a buffer for the negative impacts of shocks is crucial for policy intervention in building household resilience to food insecurity as well as for further detailed research on such a link. The intended benefits of the adoption of technologies, however, may not be realized if adoption is incomplete or mismanaged.

The second chapter uses three rounds of balanced panel data to examine the dynamic impact of multiple technology adoption on consumption expenditure, poverty, and vulnerability over time. More specifically, the study in this chapter assesses the impact of the adoption of the different combinations of five productivity-enhancing technologies (PETs) (chemical fertilizer, improved seed, and pesticide/herbicide) and soil and water conservation (SWC) practices (terracing and contour ploughing) including single technology adoption on the dynamics of consumption expenditure, poverty, and vulnerability to poverty of smallholders. Very few studies addressed the role of multiple technology adoption in reducing poverty and vulnerability to poverty as well as resilience, mainly focused on single technology adoption using cross-sectional data or in a few cases panel data (Asfaw et al., 2018; Biru et al., 2020; Perez et al., 2015; Shiferaw et al., 2008; Stige et al., 2006; Zeng et al., 2017).

The third chapter of this thesis explores the determinants of the yield of the four dominant crops (teff, wheat, maize, and barley) in Ethiopia. Using four rounds of unbalanced panel data the study examine the impact of the different combinations of PETs and SWC techniques, on the yield of these crops. Studies have shown that increased agricultural productivity is driven by the ready availability of new technologies together with improved incentives for farmers and agribusiness firms in Ethiopia (Adekunle et al., 2012). Similarly, several researchers reported that the adoption of improved agricultural practices has intended positive effects on crop yield (Ali and Abdulai, 2010; Julio and German, 2001; Thirtle et al., 2001; Zeng et al., 2015). On the contrary, yield gaps of cereal crops remain considerably larger in Ethiopia than in other SSA countries (World Bank, 2007b; Foster and Rosenzweig, 2010). For instance, though Ethiopia achieved the second-highest maize yield in SSA, maize yield is still much lower than on-farm and on-station trial yields, where only ca. 20% of the estimated water-limited potential maize yield is reported. Likewise, smallholders have only about 27% of the estimated rainfed wheat yield potential.

Among others, studies indicate that lack of access to different advanced technologies, specifically chemical fertilizer and pesticides makes up the largest component of the yield gap (Abate et al., 2018; Assefa et al., 2020; Mann and Warner, 2017; Silva et al., 2021, 2019; van Dijk et al., 2020). Agricultural technologies are complementary and smallholders apply several inputs at a time in their plots (Abate et al., 2018; Abdulai and Huffman, 2014, Kassie et al., 2018). Most agricultural technologies are also introduced and recommended to be adopted in packages. Therefore, one cannot ignore the importance of assessing the welfare effect of the adoption of the complementary inputs. Examining the impact of the adoption of multiple technologies and other determinants of yield will help to define the technological and other socio-economic constraints of smallholders in the study area in particular and Ethiopia in general.

The fourth chapter explores the link between the adoption of fertilizer and improved seeds including their joint adoption and the household’s experience to adverse shocks and resilience to food insecurity. Chemical fertilizer and improved seed are the two most widely promoted and adopted inputs intended to improve agricultural productivity and thus smallholders' welfare. As explained, rural households in Ethiopia are prone to recurring weather-related shocks such as drought, flooding, and pest infestation or human-induced shocks including conflict /political instability, animal diseases, high input prices, and imperfect product market shocks (Carter et al., 2007). The shocks, even smaller in magnitude, may have persistent effects because rural households in the country have limited capacity and resources to absorb their adverse effects. Although the shocks affect smallholders frequently the extent of damage varies from household to household depending on the wealth status, demographic structure as well as geographical location (Dercon, 2004; Dercon et al., 2005; Keil et al., 2010). Households’ drought resilience is strengthened by the possession of liquid assets, access to credit, and the level of technical efficiency in agricultural production. A study in Uganda revealed that an agricultural extension program improved smallholder farmer’s food security and better shock-copping methods (Yao et al., 2015). However, the potential benefits of agricultural technology adoption can be limited by the negative effects of shocks (Feder et al., 1985; Dercon, 2004; Dorfman, 1996; Marra et al., 2003).

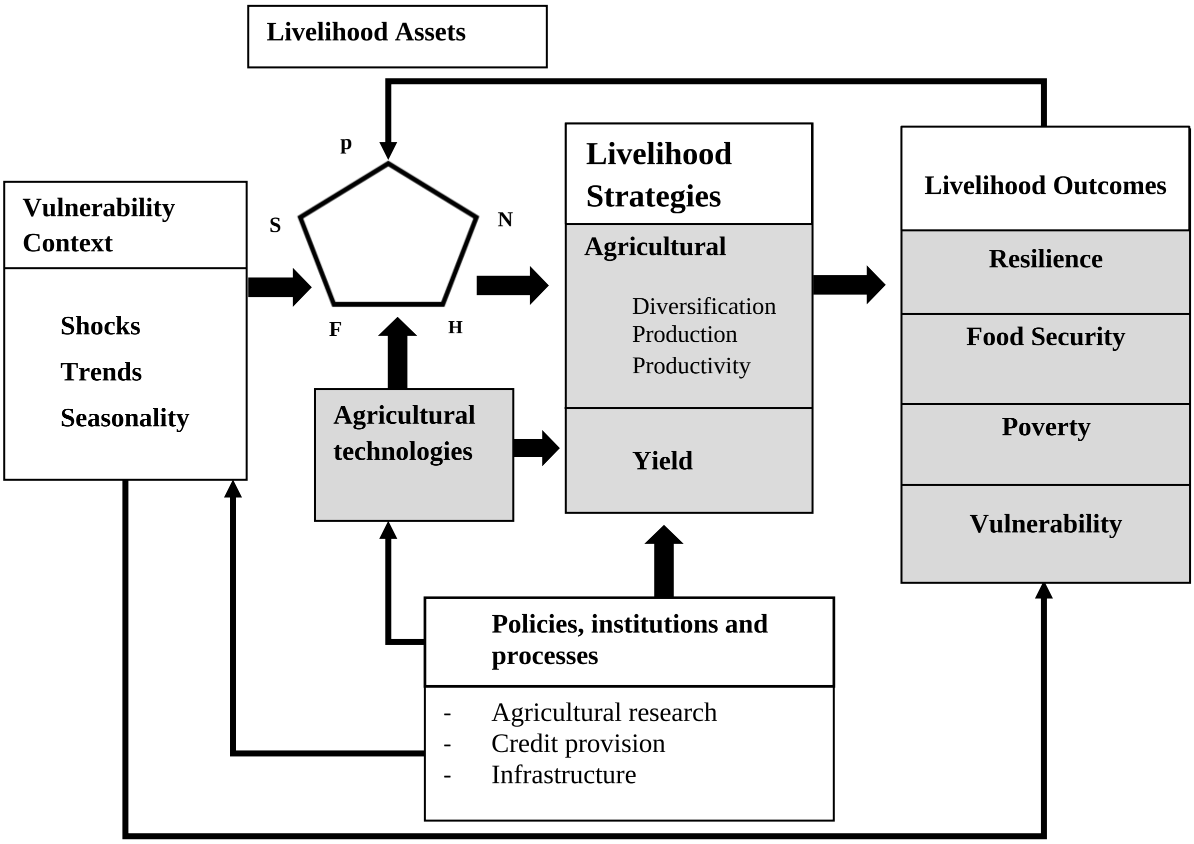
Household resilience capacity is defined as " *the ability to withstand the negative effects of shocks and return to their normal situation"*. The frequent occurrence of adverse climatic and natural shocks such as drought and flooding affects the intended benefits of adoption (Carter et al., 2007; Dercon, 2004) limiting the potential role of adoption. For instance, when drought hits, the application of chemical fertilizer may negatively affect yield and thus household welfare outcome, and in our case resilience will be affected. The approaches applied in this study better capture the multi-dimensionality of resilience to food insecurity which is appropriate for different policy interventions to improve resilience to food security. The measure of resilience capacity, its linkages with technology adoption and shocks as well as its determinants are, therefore, crucial for policy interventions intended to alleviate rural poverty and food insecurity in the country. Resilience is a dynamic and multidimensional concept. However, literature on its measurement and movements as well as its determinants is scarce mainly because of the lack of long-term panel data and partly because of the absence of a conventional measure. The rich panel data set used in our articles allows capturing the resilience index trends as well as its determinants specifically technology adoption and experience to shocks in Ethiopia. This is helpful for interventions that are meant to assist non-resilient households. The analysis gives insights on the adoption of appropriate technological combinations and their impact on welfare indicators in the face of adverse shocks that affect smallholders. Moreover, it also helps to understand why and how people become food insecure and how to build household resilience.

1.2 Conceptual Framework

To ground our analysis on a theoretical base, the sustainable livelihoods framework (SLF) (DFID, 2008) first developed by (Scoones, 1998) is adapted to conceptualize the relationship between agricultural technology, shocks, and welfare outcome variables. The conceptual framework for this thesis, which is the link between agricultural technology adoption, shocks, and the four livelihood outcomes (poverty, vulnerability, crop yield, and resilience), is depicted in Figure 1.1. Gray shaded areas indicate the linkages considered in this thesis. The framework considers five different types of assets (as depicted in the pentagon) upon which people build their livelihoods. These include physical (P), financial (F), natural (N), social (S), and human (H) capital. By combining those assets, which also include the use of agricultural technologies, rural households use different livelihood strategies to achieve their goals. The livelihood strategies are influenced by policies, institutions, and processes that in turn influence the welfare of households, in this case, poverty, vulnerability, yield, and resilience. The vulnerability context is referred to as a household's welfare insecurity in the face of changing their external environment. It can be the external impacts of shocks or an indicator of the household's internal characteristics i.e. defenselessness that is caused by the lack of means to cope with these shocks. The vulnerability context includes shocks, e.g., conflict, illnesses, floods, storms, droughts, pests, and diseases; seasonality, e.g., food shortages.

By incorporating technology adoption into the SLF, the figure presents a simplified relationship indicating how technology adoption and shocks influence livelihood outcomes, as well as the role technology adoption, may play in reducing the adverse impacts of shocks. As shown in Figure 1.1, agricultural research generates new technologies that increase agricultural production and productivity. Agricultural productivity in turn has an impact on consumption expenditure or income. The impacts of agricultural technology adoption on welfare outcomes can be direct or indirect (Julio and German, 2001; Thirtle et al., 2001). The direct effect of adopting agricultural technologies is by increasing the adopters' productivity and yield, which may be used for home consumption, or marketable surplus, improving household income and in turn reducing poverty, vulnerability and, food insecurity as well as improving resilience against adverse shocks for those households. The indirect effect of adoption may take place when improved agricultural production and productivity lead to a decrease in food prices, positively affecting both adopters and non-adopters (Julio and German, 2001). The relative importance of each of the effects for adopters depends on the extent of adoption and whether the household is a net buyer or seller (Berdegue and Escobar, 2001). Because the majority of producers in SSA countries are net buyers of food, the positive impact of productivity on poverty reduction is expected to be larger than the price effect on adopters (IFPRI, 2007).

Adopting improved agricultural technologies and practices helps households to easily deal with shocks and increase household welfare by improving resilience, and reducing vulnerability to poverty and food insecurity (DFID, 2008). Thus, by ensuring food production against extreme weather variability or other household-level shocks such as illness or the death of a family member, the adoption of agricultural innovation decreases their vulnerability and increases resilience, thereby allowing them to quickly recover if hit by shocks.



Source: DFID (2008)

*The gray shaded area shows the linkages considered in this thesis

Figure 1.1 A simple conceptual framework showing the impact of agricultural innovation systems on household welfare indicators

1.3 The Objective of the Study

The general objective of this thesis is to assess the impact of multiple agricultural technology adoption on the different welfare indicators of smallholders in Ethiopia. Furthermore, this study examines the differential effect of shocks and adoption on the resilience to food insecurity of smallholders. The specific research questions in the three interrelated articles are presented as follows.

Research topic 1: The Impact of Agricultural Technologies on Poverty and Vulnerability of Smallholders in Ethiopia: A Panel Data Analysis.

This study used three rounds of balanced panel data and employed different econometric techniques to answer the following research questions

1. What is the impact of the adoption of complementary technologies on household real food and non-food consumption expenditure?

Using household-level panel data collected in 2012, 2014, and 2016, the two-stage multinomial endogenous switching regression model combined with the Mundlak device is used to estimate the actual and counterfactual estimates of real consumption expenditure. Using the same approach the random-effects model is also executed to identify the determinants of consumption expenditure over time.

2. How is household vulnerability to poverty and its determinants?

Using three rounds of balanced panel data and the poverty transition matrix, sample households are categorized into different poverty categories, before employing an ordered logit model to estimate the impacts of technologies on the household's likelihood of being in the non-poor, vulnerable, or chronically poor category.

Research topic 2: The Impact of Agricultural Technologies on Crop Yields of Smallholders in Ethiopia: A Panel Data Analysis.

Using four rounds of unbalanced panel data collected in 2012, 2014, 2016, and 2019, the yield of the four dominant crops in Ethiopia is estimated. In terms of impact assessment, we employed endogenous switching regression models to address the unobserved heterogeneity problems of each of the four estimated yield equations and answer the specific research questions below.

1. What are the determinates of the adoption of the different combinations of agricultural technologies?

The study employed a multinomial endogenous switching regression model to address this research question.

2. To what extent does the adoption of the combinations of yield-enhancing technologies and soil and conservation practices affect the yield of main staple crops in Ethiopia?

The study employed the two-stage multinomial endogenous switching regression model combined with the Mundlak approach to estimate the impacts of the adoption of complementary inputs on the yield of the four main crops maize, teff, barley, and wheat in Ethiopia.

Research topic 3: What is the Role of Improved Technologies on Farmers' Resilience to Food Insecurity in the Face of Adverse Shocks? Evidence from Ethiopia Using Panel Data.

Using four rounds of balanced panel data, this article examines the impact of agricultural technology adoption and shocks on the dynamics of smallholders' resilience index, dietary diversity, and food consumption and access index. Specifically, this paper constructs a resilience index using four resilience pillars: And then uses the generalized dynamic models as well as lagged instrumental variable estimation to explore the link between changes in the food security indicators and the resilience index. Further, the study analyzed the impact of shocks and the adoption of chemical fertilizer or high-yielding variety and their joint adoption on the resilience index.

1. How is household resilience capacity and how is it composed?

Using four rounds of pooled panel data and employing the SEM-MIMIC model a resilience index is constructed using four resilience pillars.

2. What is the impact of shocks and the differential impact of the adoption of multiple technology adoption on the resilience index over time and are the most important coping strategies applied by smallholders when hit by shocks?

To solve the presence of potential reverse causality between technology adoption and resilience index, lagged dependent instrumental variable regression model is employed to estimate the impact of the adoption of chemical fertilizer and improved seed or their joint adoption on the resilience index. The mixed Tobit and GMM regression models are also executed for comparison and robustness check.

1.4 Data and Study Area

Our data come from four waves of farm household surveys collected from 400 households that are drawn from 2012 nationally representative baseline survey conducted by the International Food Policy Research Institute (IFPRI) and Agricultural Transformation Agency (ATA) in Ethiopia. The baseline survey covers the four main regions of Ethiopia, namely Tigray, Amhara, Oromia, and Southern Nations Nationalities and Peoples Region (SNNPR). In their sampling procedure, the ATA/IFPRI specifically used a three-stage stratified random sampling procedure (David et al., 2012; Minot and Sawyer, 2013). In the first stage, 100 woredas (districts) were randomly selected. In the second stage, two kebelles[1]. were randomly selected

[1] The smallest administrative unit of Ethiopia

from each of the 100 woredas. And thirdly, fifteen farm households were randomly selected from each of the 200 Kebelles. The total sample size for the baseline survey is, therefore, 3000.

Our analysis relies on those sample households drawn from the ATA/IFPRI baseline survey households that are located in Southern Ethiopia covering part of and SNNPR and Oromia region. From those two regions, we considered 15 representative woredas, and 2 Kebelles from each of the woredas except Agarfa where we had to drop one of the Kebelles due to security issues during the 2014 survey round. The Woredas (clusters) were selected in such a way that the major climatic and agro-ecological variations of the country were included. Nine of the 15 woredas are located in SNNPR and the remaining 6 are located in the Oromia region. For our analysis, we used three rounds of panel data with a total sample of 390 households. The first round data come from the 2012 baseline survey and we conducted the second and third rounds in 2014 and 2016 tracking the same panel of 390 farm households. Our sample households are limited to only two of the four regions because of budget and logistical constraints. However, our sub-sample farm households are diverse in terms of climatic and agro-ecological characteristics and in turn agricultural production. Figure 1.2 depicts the study area. The attrition rate between 2012 and 2014 is zero whereas the attrition rate between 2014 and 2016 is 2.5%; the systematic attrition rate was tested and there is no significant difference in the regression analysis (with attrition and without attrition). Both the follow-up rounds and the baseline survey questionnaire have rich information on demography, asset ownership, technology and input use, consumption, production, and health.

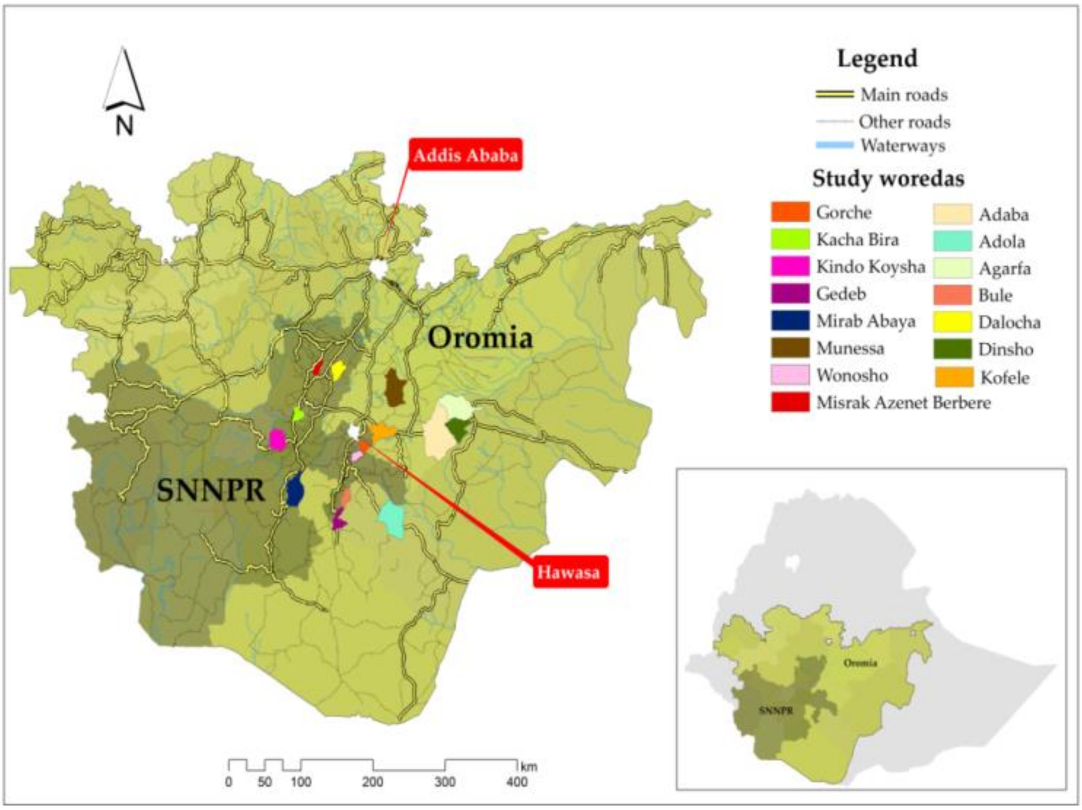


Figure 1.2 Map of the study area

1.5 Outline of the Thesis

The thesis is structured into five chapters. After an introductory chapter (chapter 1) that states the problem background, presents the conceptual framework and introduces the main research questions addressed in the thesis, introduces the study area and data used. Chapters 2 and 3 contain research on the impacts of agricultural technologies on the welfare outcomes of smallholders, chapter 4 presents the measure of resilience capacity and its determinants. Chapter 5 summarizes research findings, discusses them, and concludes.

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Chapter Two

2. The Impact of Agricultural Technologies on Poverty and Vulnerability of Smallholders in Ethiopia: A Panel Data Analysis

Wubneshe D.Biru, Manfred Zeller, Tim K.Loos

(The article contained in this chapter is published in Social Indicators Research 2019, Vol. 148, No. 35,518-544, https://doi.org/10.1007/s11205-019-02189-7)

Abstract

Many studies evaluating the impact of adoption on welfare focused on the adoption of a single technology giving little attention to the complementarity/substitutability among agricultural technologies. Yet, smallholders commonly adopt several complementary technologies at a time and their adoption decision is best characterized by multivariate models. This paper, therefore, examines the impact of multiple complementary technologies adoption on consumption, poverty, and vulnerability of smallholders in Ethiopia. The study used balanced panel data obtained from a survey of 390 farm households collected in 2012, 2014, and 2016. A 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. An ordered probit model is used to analyze the impact on poverty and vulnerability. We find that the adoption of improved technologies increases consumption expenditure significantly and the greatest impact is attained when farmers combine multiple complementary technologies. Similarly, the likelihood of households remaining poor or vulnerable decreased with adoption the adoption of different complementary technologies. We, therefore, 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.

Keywords: vulnerability, poverty, technology adoption, Ethiopia, panel data

2.1 Introduction

Sub-Saharan Africa (SSA) has the highest number of people living in extreme poverty, comprising 413.3 million people in 2015 (Beegle et al., 2016). The number has grown substantially since the 1990s and about 88% of the world's poorest are expected to live in Africa by 2030 (World Bank, 2015). In Ethiopia, about 33% of the rural population lives below the national poverty line and an additional 14% of non-poor households are estimated to be vulnerable to falling into poverty (World Bank, 2015). Non-poor households are vulnerable to poverty because of their exposure to various types of shocks and their lack of coping mechanisms (Dercon, 2004). As a result, improving agricultural productivity growth is considered key to alleviating poverty and vulnerability[2] of smallholder farmers. This is because the majority of the rural population depends on rain-fed subsistence agriculture with limited use of improved agricultural technologies. Ethiopia's agricultural sector makes up the lion's share of the national economy, accounting for about 43% of GDP, 90% of exports, and 96% of rural employment. Despite this importance, agricultural productivity in the country is low; it is constrained by recurrent droughts, erratic rainfall, declining soil fertility, missing or imperfect input and output markets as well as limited access to improved technologies (Abebe and Sewnet, 2014; Asfaw et al., 2011; Doss and Morris, 2000; Misiko and Ramisch, 2007; Pender et al., 2006).

Since 1992, the government of Ethiopia has implemented Agricultural Development Led Industrialization (ADLI), an economic growth strategy, in response to the poverty and food security challenges of the country. As indicated by the Ministry of Finance and Economic Development (MoFED), the ADLI policy focuses mainly on strengthening the interdependence between agriculture and industry by increasing the productivity of smallholder farmers through better agronomic practices, research and extension, technology transfer, and rural infrastructure (MoFED, 2003). Consequently, regional and national research institutes in the country have released a number of improved agricultural technologies in crops, livestock, and natural resource management practices over the past two decades. The intervention has enabled relatively higher proportions of farmers to adopt improved crop production technologies in some areas of the country (Doss et al., 2003; Mandefro et al., 2002; Tadesse and Degu, 2002). Moreover, the recent Growth and Transformation Plans (GTP I and GTP II) of the country also gives special emphasis to the notion of resource management based agricultural systems at the policy level. However, the introduction and adoption of those technologies have had only partial

[2] In this paper, vulnerability refers to "vulnerability to poverty".

success, as measured by observed rates of adoption in the country. For instance, Spielman et al. (2011) reported that only 30-40% of Ethiopian smallholders apply fertilizer in their field, and their application, which is only 37-40 kilograms per hectare, is usually far below the recommended rates. Using nationally representative household data, Minot and Sawyer (2013) found slightly higher rates of fertilizer use (56%) among smallholders in Ethiopia both belg and meher seasons in the 2012 agricultural year. The same study further revealed a similar trend (56%) on the use of purchased seed (even though it doesn't necessarily mean improved seed), and 31% of the farmers apply pesticides in the same agricultural year. Yu and Pratt (2014) reported that the adoption rate of the new technology packages released in Ethiopia increased from 42% in 2003 to 48.5% in 2006 then fell below 47% in 2007. The adoption of soil and water conservation practices by smallholders also remains very low in the country due to inadequate information on the technical details of the technology, low short-term benefits, decrease in total cultivable area, and labor requirement (Wolka, 2014; Asfaw and Neka, 2017). Since improved agricultural technologies play an important role in fighting poverty and vulnerability to poverty, it is important to assess to what extent their impact on the different wealth categories of smallholders.

The effectiveness of productivity enhancing technologies (PETs), such as chemical fertilizer and improved seed, depends on the type of soil and water availability (Kassie et al., 2013). With almost negligible use of irrigation and water harvesting technologies in the region, water scarcity is one of the major constraining factors of agricultural productivity in Ethiopia. Therefore, it is important to complement the PETs with improved soil and water conservation (SWC) practices, such as terracing. The SWC practices help smallholders protect against the high levels of soil depletion and erosion problems observed in the region (Mango et al., 2017). The SWC practices improve soil fertility and preserve water, which in turn increases the effectiveness of yield enhancing technologies and consequently increases crop productivity. Studies, such as Kassie et al. (2013), clearly show that soil conservation and water harvesting practices play a crucial role in sustaining crop yields by increasing soil moisture.

Several studies show a significant positive impact of improved agricultural practices on the welfare of smallholders (Abebe and Sewnet, 2014; Ali and Abdulai, 2010; Asfaw et al., 2012; Bezu et al., 2014; Kassie et al., 2018; Manda et al., 2016). According to Diao (2010), for instance, a 1% annual increase in Ethiopia's GDP driven by agricultural growth leads to a 1.78% reduction in the country's poverty headcount rate per year. A study by Janvry and Sadoulet (2002) showed that the adoption of agricultural technologies affect poverty and vulnerability to poverty directly or indirectly. The direct impact is through improving agricultural productivity, which leads to an increase in home-consumed food and marketable surplus, which in turn reduces the poverty and vulnerability of adopters. An indirect effect may be achieved through a reduction in food prices for non-adopters and net buyers of food. Enhancing agricultural productivity, particularly for important staple crops in the region such as teff, maize, wheat, and barley improves supply and reduces the staple food price, and in so doing helps to lift the poor above the poverty line (Christiaensen and Subbarao, 2005; de Janvry and Sadoulet, 2002; Diao, 2010).

In this paper, we assess the impact of the adoption of PETs, including chemical fertilizer, improved seed variety, and pesticides, and SWC practices, including terracing and contour ploughing, on consumption, poverty, and vulnerability of smallholders in Ethiopia. These technologies are popular practices in the study area (Di Falco and Bulte, 2013). There is extensive literature assessing the impact of adopting a single technology on the welfare of farmers (see Asfaw et al., 2012; Becerril and Abdulai, 2009a; Bezu et al., 2014; Hailu et al., 2014; Kassie et al., 2018; Verkaart et al., 2017). In fact, agricultural technologies are mostly introduced and recommended to be used with other complementary inputs (Dercon et al., 2009; Howard et al., 2003; Spielman et al., 2010) and the maximum potential can only be reached when interrelated technologies and complementary practices are implemented simultaneously (Abdulai and Huffman, 2014; Kassie et al., 2018). Few studies assessed the impact of adopting multiple technologies jointly on the welfare of farmers (Kassie et al., 2013; Teklewold et al., 2013). Of those few studies, even fewer analyzed the dynamic impact of the technology combinations. Hence, the main objective of this article is to estimate the impact of PETs and SWC measures and their possible combinations on changes in consumption, poverty, and vulnerability to poverty over time.

This introduction is followed by a description of the conceptual framework and estimation strategy that form the theoretical and empirical basis for the econometric analyses. After describing the data and explanatory variables, the empirical results are discussed. Finally, conclusions and recommendations based on the major findings are presented.

2.2 Conceptual Framework and Estimation Strategy

An individual farmer in Ethiopia is both a food producer and a consumer, i.e., smallholders are involved in both production and consumption decisions. Smallholder farmers in Ethiopia, like any other rural households in developing countries, are faced with various constraints such as imperfect or missing input and credit markets, high transaction costs, and unemployment. With the presence of such market failure in rural areas where farmers consume a significant proportion of their outputs and supply a significant proportion of factor input, assuming consumption and production decisions as independent is erroneous. Rural households are endowed with five different types of assets upon which they build their livelihoods. These assets include physical, financial, natural, social, and human capital. Households, therefore, employ different combinations of assets in order to maximize their utility. On the other hand, their livelihood strategies are influenced by external factors such as agro-climatic conditions, pests and diseases, policies, institutions, and processes that in turn influence the productivity of households. The introduction of agricultural technologies such as chemical fertilizer and improved seed variety or the promotion of improved SWC practices affect the farmers' perception, expectation, and preference toward different varieties and inputs used in production. These in turn will condition their decisions in terms of investment, crops and varietals choice, and resource allocation to various inputs (Asfaw et al., 2011). Supposedly, this would affect a household's level of consumption for food and essential non-food items, the marketable surplus of different crop varieties, savings, and income generation activities. Therefore, household decisions and choice constitute their behavioral outcomes which will finally affect their consumption expenditure (welfare outcomes). Thus, by ensuring food production against extreme weather events and household-level shocks, such as illness or the death of a family member, the adoption of improved PETs combined with SWC practices is crucial in improving the resilience of farmers and decreasing vulnerability to poverty. In general household models are non-separable and household resource allocation including off-farm labor supply is determined simultaneously rather than recursively (de Janvry et al., 1991).

We model the adoption decision behavior of farmers at time *t* following Kassie et al. (2015) and Abdulai and Huffman (2014) where the adoption decision is modeled in a random utility framework. In this framework, smallholders are assumed to maximize their utility function subject to the different resource constraints. Given a set of agricultural technology choices, rural households face various constraints in their adoption decision process. In this paper, based on the aforementioned literature, we assume that smallholder farmers adopt a technology set *m* at time *t* to maximize utility, max u_{it} = f(x_{it}) subject to the various adoption constraints, where x is the explanatory variables affecting the adoption decision of the farmer.

An individual farm household considers adopting a single improved technology or a set of improved technologies if the expected utility from adoption E(U_{itA}) is higher than the expected utility from non-adoption E(U_{itN}). Farmers are therefore assumed to choose the combination of technologies that provides maximum expected utility. In other words, the difference between the expected utility from adoption and the expected utility from non-adoption denoted as Y^* such that a utility maximizing farm household *i* will consider adopting a set of technologies if the expected utility obtained from adopting is greater than the expected utility from non-adoption (Y^*=E(U_{itA})- E(U_{itN})>0). Since the utilities gained are unobservable, it can be expressed as the following latent variable model:

$$Y_{itm}^* = \beta X_{itm} + \mu_i \qquad where\ \ Y_{itm} = \begin{cases} 1 & if \quad Y_{im}^* > 0 \\ 0 & otherwise \end{cases} \qquad m = 1,2..M \tag{1}$$

where *Y* is an observable categorical indicator variable that equals 1 if the farmer adopted a single technology or set of technologies and zero for non-adoption; β is a vector of parameters to be estimated; *X* is a vector of explanatory variables, and μ is the error term.

To evaluate the impact of adoption on welfare, in our case, the outcome variable of interest is per capita consumption expenditure in real terms, assumed to be a linear function of observed household and plot characteristics along with the technology adoption categorical variable. Using panel data, the outcome equation can be written as:

$$\mathrm{lnc}_{it} = \beta X_{it} + \eta I_{it} + \alpha_i + \varepsilon_{it} \tag{2}$$

where lnc_{it} represents the logarithm of real per capita consumption at time t and for the i[th] household; β dontes vector of coefficients; X_{it} represents vector of explanatory variables for household *i* at time *t* ; *I*, in this case, is a categorical variable (*I*=1,2….M if the household adopted the technology set; *I*=0 if none of the technologies are adopted); η = measures the effect of the technology; α_i = unobserved household specific fixed effects assumed to be fixed over time but vary across household *i*; ε_{it} is the error term. Therefore, for this model, the effect of improved technology is the estimate ofη. However, the categorical variable I cannot be treated as exogenous if the decision of an individual to adopt or not to adopt is based on individual self-selection (Maddala, 1983; Wooldridge, 2010). Therefore, evaluating the impact of technology adoption is challenging, since the counterfactuals are unobserved, that is we do not observe what would have happened had the farmer did not adopt technologies leading to potential selection bias and unobserved heterogeneity (Heckman, 1979). Thus, analyzing the impact of technologies on welfare requires controlling for unobserved heterogeneity and potential selection bias. Selection bias arises when technology adoption is voluntarily decided or some technologies are targeted to a given group of farmers. For instance, more relatively wealthy farmers could be those who adopt modern technologies; in this case, self-selectivity into technology adoption is the source of endogeneity (Hausman, 1978). This problem can be commonly solved by using an instrumental variable regression model. Alternatively, with the availability of panel data, a panel data estimator solves the problem without an instrumental variable. However, this can only be attained if the selection process is based on time-constant unobserved heterogeneity (Maddala, 1983; Wooldridge, 2010). As explained, however, the selection process might be generated by time-varying unobserved heterogeneity that affects the outcomes (Wooldridge, 2010). In such a case, the availability of panel data alone is insufficient and the estimates of the fixed effects or random effects models are inappropriate. To solve this problem, we combine a panel data estimator with an endogenous switching regression (ESR) model that enables us to capture time-varying unobserved heterogeneity (Abdulai and Huffman 2014; Kassie et .al 2018).

2.2.1 Two-Stage Endogenous Switching Multinomial Logit Regression Model

Following Kassie et al. (2018), we estimated a two-stage endogenous switching multinomial logit model (ESMNL). Assuming a technology set *m*, *m* is equal to 1 if the household adopted a combination of technologies or only a single technology and 0 if otherwise; and the utility function that ranks the i^{th} household's preference for these improved technologies by U(L_{mi},R_{mi}), utility depends on a vector of L_m of moments that describe the distribution of technology set *m*, including adoption cost and a vector R_m of other attributes associated with the technology (Di Falco et al., 2012; Kassie et al., 2018). The variables L_m and R_m are unobservable, but a linear relationship is postulated for the i^{th} household. The ESR model also allows the technology set choices (treatment variables) to interact with observable variables and unobserved heterogeneity. This means that the effect of technology choice is not limited to the intercept of the outcome equations, (see Zeng et al., 2015), but can also have a slope effect[3].

We estimate the pooled OLS following Wooldridge (2002) and pooled selection models using the Mundlak (1978) approach. We included the means of the time-varying explanatory variables as additional explanatory variables in both the outcome and adoption equations so as to control for unobserved heterogeneity (Mundlak 1978). The Mundlak device combines the fixed-effects and random effects estimation approaches. By including, the mean of time-varying explanatory variables, we control for time-constant unobserved heterogeneity, as with fixed effects, while avoiding the problem of incidental parameters in nonlinear models such as the

[3] We used a chow test to see if the different combined practices have significantly different slopes.

multinomial logit (MNL) model. Using the three round balanced data, we also run the random effects model using the Mundlak approach controlling for unobserved time-varying heterogeneity. The estimation of multinomial switching endogenous regression framework involves a two-step estimation procedure. In the first step, a MNL model accounting for unobserved individual heterogeneity is estimated to generate the inverse Mills ratio. For the MNL model, the IIA assumption is met (Dubin and McFadden, 1984). Previous empirical studies that evaluated the impact of adoption using an endogenous switching regression include Di Falco et al. (2011), Teklewold et al. (2013), Abdulai and Huffman (2014), and Kassie et al. (2015, 2018).

The adoption of five technologies and their combinations involves 32 possible technology choice sets (including an "empty" set for non-adoption). We specified 32 equations for each technology choice set. However, we combined some of the technology choice sets because of insufficient observations for most of the practices and many of the potential combinations were not observed in our sample households. After the different tests[4], we finally reduced the number of outcome equations to nine technology choice sets including the "empty set" for non-adoption.

The five technologies with their combinations considered here are: PETs include chemical fertilizer, improved seed variety, and pesticide and SWC measures include terracing and contour ploughing. These technologies are commonly practiced in the study area. As mentioned above, we base our analysis on the latent variable concept, where we assume that each time period the household chooses a technology set that maximizes the expected utility. Let a farm household choosing a technology set m (m=0,1,2,…,6) and j=0 denoting that none of the practices were adopted, while the remaining technology sets (m=1,2,…,6) contain at least one technology be represented by u_{mt}. A farm household chooses a technology set *m* if and only if its expected utility u_{mt} is greater than the expected utility (u_{kt}) that could be obtained from other technology sets including the non-adoption option, i.e. $u_{mt}>u_{kt}$, $m \neq k$.

Following Kassie et al. (2015), we specify the utility of adoption as a function of exogenous variables including household, plot characteristics averaged at household level as well as regional and time dummies. The probability that a farm household adopt technology set m time t conditional on x_{it} can be represented as:

[4] For the independence of the different technology combinations, we used the Stata user command mlogtest to test the possibility of combining related technologies in MNL model and the chow test commands to test for slope differences in the outcome equations.

$$\text{prob}\left(j \middle| X_{it}, Z_i = \frac{\exp(a_i + X_{it}\beta_m + Z_i)}{\sum_{k=1}^{m} \exp(a_k + X_{it}\beta_k + Z_i)}\right), m = 0,1,2 \ldots 6 \tag{3}$$

where i represents individual farmer; *m* represents technology set and *t* represents time period; a_m is the specific constant term of technology set m; X_{it} represents a matrix of observable explanatory variables that affects the probability of adoption, Z_i denotes time constant unobserved heterogeneity term and β_m represents unknown parameters to be estimated. As discussed above, the unobserved heterogeneity (Z_i) will be replaced by means of the time-varying explanatory variable (X_i), following the Mundlak approach. Equation (3) is estimated using MNL model based on household level balanced panel data. To implement the Mundlak approach, we include the means of all time-varying covariates. In the second stage ESR, the consumption function is estimated for adopters and non-adopters separately controlling for the endogenous nature of technology adoption decisions. The seven consumption expenditure equations are specified as follows:

$$\begin{cases} \text{Regime } 0: \ln C_{it0} = V_{it0}\beta_0 + \lambda_{it0}\sigma_0 + H_{i0} + \varepsilon_{it0} & \text{if } m = 0 \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . & \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . & \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . & \\ \text{Regime } m: \ln C_{itM} = V_{itM}\beta_M + \lambda_{itM}\sigma_M + H_{iM} + \varepsilon_{itM} & \text{if } m = M, 1,2 \ldots\ldots 6 \end{cases} \tag{4}$$

where m = 0 denotes that neither of the technologies nor their combinations were adopted and m = 1, . . . 6 represents adoption of either technology or their combinations; lnC_{itM} denotes the consumption expenditure for household *i* at time *t* with technology and $\ln C_{it0}$ represent the consumption expenditure for household *i* at time *t* with no adoption. V_{it} denotes observable household, plot and village characteristics, including a time period dummy (*T*), that influence consumption expenditure at time *t*; β and σ are parameters to be estimated and the covariance between the error terms and adoption and outcome equations, respectively. H_i is the time invariant unobservable household heterogeneity; $\hat{\hat{\lambda}}$ is inverse Mills from equation (3) to capture time-varying individual effects (Dubin and McFadden, 1984). As in the choice model, the time invariant unobserved variable ($\overline{H}$) is parameterized by the mean values of time-varying explanatory variables $\overline{Z}$ Time period and regional dummies are included in our estimation to capture temporal and spatial differences in agro-ecology, price and institutions.

2.2.2 Expected Actual and Counterfactual Outcomes

The estimated treatment effects are of particular interest in this context, specifically the average treatment effect (ATE) and the average treatment effect for the treated (ATT). The ATE is defined as the effect of treatment on a person selected at random from the given population relative to the effect on that person had he or she not received the treatment. This is the difference between the treated and untreated state for a given person (Gregory, 2015) . After estimating the consumption equation, the next step is computing the expected and counterfactual outcomes. This is important to explicitly evaluate the causal effect of improved technology adoption. The actual expected outcomes that are observed in the data are computed as:

$$E(\ln C_{itM}|m = M) = V_{itM}\beta_M + \lambda_{itM}\sigma_M + \hat{V}_{iM}\omega_M \tag{5}$$

On the other hand, the counterfactual expected value of consumption expenditure for household i with a technology set m that contains one or more improved technologies is given as follows:

$$E(\ln_{it0}|m = M) = V_{itM}\beta_0 + \lambda_{itM}\sigma_0 + \hat{V}_{iM}\omega_0 \tag{6}$$

where the parameters β_0, σ_0 and ω_0 are coefficients obtained from the estimation of consumption expenditure without a technology set (m = 0) and other variables are as defined above. Taking the difference between equations (5) and (6) gives the average effect of technology on adopters, often described in the literature as the average treatment effect on the treated (ATT). The ATT can be derived as:

$$\begin{aligned} ATT_{ym} &= E(\ln C_{it1}|m = M) - E(\ln C_{it0}|m = M)) \\ &= (\beta_m - \beta_0)V_{itm} + (\sigma_M - \sigma_0)\lambda_{itM} + (\omega_M - \omega_0)\hat{V}_{iM} \end{aligned} \tag{7}$$

The first two terms of equations (7) indicate consumption expenditure change due to the difference in returns to observed characteristics and time-invariant unobserved characteristics, respectively, and the last term attributes to changes in consumption because of time-varying unobserved heterogeneity difference.

The consumption expenditure calculation focuses on food expenditure and includes both own production and purchased food, purchased meals, and non-investment non-food items (Dercon et al. 2005). Taxes, rents, contributions to durable goods, and health and education expenditures are not included in the calculation. Furthermore, the real per capita consumption expenditure[5] is deflated by the food price index using the 2012 prices as a base. The present analysis is performed on three rounds of balanced household panel datasets spaced two years apart.

[5] The consumption data are based on summing the expenditures of all sources of food and non-food consumption, deflated by a consumer price index, using 2012 as the base. It is expressed in monthly per capita units in ETB. The national poverty line in 2011/2012 prices is 3,781 ETB/adult/year, thus the per capita monthly expenditure in this case is ETB 315.

2.2.3 Measure of Poverty and Vulnerability

It is expected that the adoption of improved technologies and SWC contribute to poverty reduction through improving income and level of food security of smallholder farmers in most developing countries (Asfaw et al., 2012; Becerril and Abdulai, 2010; de Janvry and Sadoulet, 2002). Using per capita consumption expenditure and the national poverty line, which is ETB[6] 315 per month per person in 2011 prices, we categorize households into poor and non-poor. We use the empirical measure of poverty proposed by (Foster et al., 1984). Poverty at time t=1,…,T in a population of n households with incomes or consumption $y_{1t}<y_{2t}<y_{nt}$ is:

$$p_{\alpha t} = \frac{\sum_{i=1}^{m_t}\left(\frac{z-y_{it}}{z}\right)^{\alpha}}{n} \tag{8}$$

where $y_{it} \leq z$ if $i \leq m_t$. Note that for α=0, the measure is simply the head count index. For α=1 it is the poverty gap, averaged over the population and expressed as a proportion of the poverty line. Note that in this paper we focus on the World Bank's definition of poverty, "pronounced deprivation in well-being". Therefore, according to the definition, poor households are those that do not have enough income or consumption to put them above the national poverty line, which is the adequate minimum threshold. The poverty line is the minimum amount of money required to afford the food that meets minimum caloric intake requirements and essential non-food items World Bank (2005). For this study we use the national poverty line of Ethiopia, which is ETB 3,781, using 2011 prices.

According to Hoddinott and Quisumbing (2010), Moser (1998) and Alwang et al. (2001), poverty and vulnerability can be distinguished as the latter incorporates uncertainty. Therefore, we use different approaches to measure vulnerability. Vulnerability is defined as the likelihood that at any given time in the future, an individual will have a level of welfare below some norm or benchmark. In the simplest case, given the current condition, vulnerability measures the probability of falling below the poverty line in a given time horizon (Baker, 2000). Vulnerability as uninsured exposure to risk (VER), vulnerability as low expected utility (VEU) and vulnerability as expected poverty (VEP) are three conceptual approaches used to measure vulnerability (Hoddinott and Quisumbing, 2003). The VEP and VEU approaches are ex-ante analysis and require cross-sectional data. They predict the probability of being poor in the future based on the current level of consumption. The VER requires panel data. In the absence of panel

[6] 1 US $ was equivalent to ETB 18.01 (July 2012).

data, one can analyze vulnerability to poverty by using predicted probabilities and the consumption attached to those values. With panel data, we use the actual distribution of consumption of the sample households and analyze the movement of households in and out of poverty by using the poverty transition matrix.

Poverty assessment helps us to measure the effects of past interventions on welfare and allows us to identify who is poor at a point in time (Haughton and Khandker, 2009). However, the well-being of a household depends not only on its current income or consumption but also on its exposure to different types of shocks. Due to uncertain income or consumption, households that are non-poor this year may fall into poverty next year. Similarly, a household that is poor this year may or may not escape poverty next year. As a result, it is very important to categorize households based on their past and current income/consumption level and then identify households as vulnerable, chronically poor, or non-poor (Haughton and Khandker, 2009). In our case, the movement of households in and out of poverty between 2012 and 2016 is assessed using a poverty transition matrix presented in Table 2.2. The result of the matrix, which is a cross-classification of the households' poverty status at different points in time, is shown in the results section (see Table 2.2).

2.2.4 Estimating the Impact of Technologies on Poverty and Vulnerability

Using real per capita consumption expenditure in each round, households are divided into three poverty categories: chronically poor, vulnerable, and non-poor. We assumed that the poverty categories can be ordered since we base our classification on the level of real per capita consumption expenditure where the chronically poor situation is the worst to be in and the non-poor category is the best situation. The objective is to analyze the impact of the technology sets mentioned above on the different poverty profiles of households. The ordered probit model is used to analyze the effect of the technology variables on poverty and vulnerability. We specified the model following Long and Freese (2014) and Wooldridge (2002). The ordered response variable has three outcomes taking the value 1 if the household is poor during all the three rounds, 2 if the household is poor at least once and 3 if the household is non-poor for all rounds of the panel. The ordered response variable (y) conditional on the explanatory variables (x) can be derived from the latent variable model. Assume that the latent variable y* is determined by:

$$y^* = x\beta + e, e|x \sim \text{Normal}(0,1) \quad (9)$$

Where β is a K x 1 and, for reasons x does not contain a constant. In our case with three categorical variables, we will have two cut points. Given the standard normal distribution for e, the conditional distribution of y given x can be computed as:

$$\mathrm{p}(\mathrm{y}=1|\mathrm{x}) = \mathrm{p}(\mathrm{y}^* \leq \mathrm{k}_1|\mathrm{x}) = \mathrm{p}(\mathrm{x}\beta + \mathrm{e} \leq \mathrm{k}_1|\mathrm{x} = \Phi(\mathrm{k}_1 - \mathrm{x}\beta)$$
$$\mathrm{p}((\mathrm{y}=2|\mathrm{x}) = \mathrm{p}(\mathrm{k}_1 \leq \mathrm{y}^* \leq \mathrm{k}_2|\mathrm{x}) = \mathrm{p}(\mathrm{x}\beta + \mathrm{e} \leq \mathrm{k}_1|\mathrm{x} = \Phi(\mathrm{k}_2 - \mathrm{x}\beta) - \Phi(\mathrm{k}_1 - \mathrm{x}\beta)$$
$$\mathrm{p}(\mathrm{y}=3|\mathrm{x} = \mathrm{p}(\mathrm{y}^* \geq \mathrm{k}_3|\mathrm{x}) = \mathrm{p}(1 - \Phi(\mathrm{k}_{13} - \mathrm{x}\beta) \qquad (10)$$

The sum of the probabilities gives unity. The parameters k and β can be estimated by maximum likelihood. In the present paper, we are interested in how ceteris paribus changes in the elements of technology adoption affect the response probabilities, P(y=j|x), j=1,2,..j). The partial effects of the explanatory variables on the different categories can be computed as:

$$\frac{\partial \mathrm{y}_0(\mathrm{x})}{\partial \mathrm{x}_\mathrm{k}} = -\beta_\mathrm{k}?(\mathrm{k}_1 - \mathrm{x}\beta), \frac{\partial \mathrm{p}_\mathrm{J}(\mathrm{x})}{\partial \mathrm{x}_\mathrm{k}} = \beta_\mathrm{k}?\left(\mathrm{k}_\mathrm{J} - \mathrm{x}\beta\right) \qquad (11)$$

$$\frac{\partial \mathrm{y}_\mathrm{j}(\mathrm{x})}{\partial \mathrm{x}_\mathrm{k}} = \beta_\mathrm{k}\left[?\left(\mathrm{k}_{\mathrm{j}-1} - \mathrm{x}\beta\right) - ?((\mathrm{k}_\mathrm{j} - \mathrm{x}\beta)\right], \qquad 0 < \mathrm{j} < \mathrm{J}$$

Where y_i represents three household ordered poverty categories of poverty transition:

- Y_0 households that are under the poverty line in all the three periods will be given a value of 1 (chronically poor);
- Y_1 households that have changed their status at least once during the three periods will be given a value of 2 (vulnerable) and
- Y_2 households that are always non-poor (whose consumption level is persistently above the poverty line) will be given a value of 3 (always non-poor)

A Brant test for parallel regression/proportional odds assumption is tested. The Brant test statistic is not significant providing evidence that the parallel regression assumption has not been violated.

2.3 Data and Description of Explanatory Variables

2.3.1 Data and Study Area

Our data come from three waves of farm household survey collected from 390 households that are drawn from the 2012 nationally representative baseline survey conducted by the International Food Policy Research Institute (IFPRI) and Agricultural Transformation Agency (ATA) in Ethiopia. The baseline survey covers the four main regions of Ethiopia, namely Tigray, Amhara, Oromia and Southern Nations Nationalities and Peoples (SNNPR). In their sampling procedure, the ATA/IFPRI specifically used a three-stage stratified random sampling procedure (David et al., 2012; Minot and Sawyer, 2013). In the first stage, 100 woredas (districts) were randomly selected. In the second stage, two kebelles[7] were randomly selected from each of the 100 woredas. And thirdly, fifteen farm households were randomly selected from each of the 200 kebelles[8]. As a result, the total sample size for the baseline survey is 3000.

Our analysis relies on those sample households drawn from the ATA/IFPRI baseline survey households that are located in Southern Ethiopia covering part of SNNPR and Oromia region. From those two regions, we considered 15 representative woredas, 2 Kebelles from each of the woredas except Agarfa where we had to drop one of the Kebelles due to security issues during the 2014 survey round. The Woredas (clusters) were selected in such a way that the major climatic and agro-ecological variations of the country were included (See Appendix Table A2). Nine of the 15 woredas are located in SNNPR and the remaining 6 are located in Oromia region. For our analysis, we used three rounds of panel data with a total sample of 390 households. The first round data come from the 2012 baseline survey and we conducted the second and third rounds in 2014 and 2016 tracking the same panel of the 390 farm households. Our sample households are limited only in the two of the four regions because of budget and logistical constraints. However, our sub-sample farm households are diverse in terms climatic and agro-ecological characteristics and in turn agricultural production. We used a balanced panel data regression analysis; and the attrition rate between 2012 and 2014 is zero whereas the attrition rate between 2014 and 2016 is 2.5%; the systematic attrition rate was tested and there is no significant difference in the regression analysis (with attrition and without attrition). Both the

[7] One of the Kebelles in Agarfa Woreda (Oromia region) was dropped because of accessibility and security issues we faced during the 2014 survey round.
[8] The smallest administrative unit of Ethiopia

follow up rounds and the baseline survey questionnaire have rich information on demography, asset ownership, technology and input use, consumption, production, and health.

2.3.2 Description of Explanatory Variables

In this sub-section, we explain our prior expectations regarding the relationships between the explanatory variables included in the model and consumption, poverty and vulnerability of rural households.

Technology choice sets: The five technologies and practices included in this study (chemical fertilizer, pesticides, improved seeds, terracing, and contour ploughing) and their combinations measured as dummy variables taking the value of 1 if the household adopted the technologies in any of their plots and 0 otherwise (see Table 2.1, are all expected to increase agricultural output and productivity. This increase in production should lead to increase in consumption as well as reduction in poverty and vulnerability. However, in the case of severe shocks leading to a complete crop failure, the adoption of chemical fertilizer, for instance, may cause households to suffer large financial losses, because of input costs spent. To improve the resilience of crops to climatic shocks, and at the same time improve soil fertility, different SWC techniques may prove useful. For example, mulching, composting and contour ploughing are assumed to increase soil organic matter and water holding capacity, leading to improved crop productivity. This, in turn, should lead to higher food availability and income available for consumption, leading to reduced poverty. Despite the high investment costs of SWC practices like terracing, it is supposed that the long-term effects will lead to increased consumption and reduced poverty and vulnerability.

Number of livestock and farm size: Possession of livestock and farm size as indicator variables for wealth are used to capture the impact of household wealth on adoption and welfare. The number of livestock representing asset ownership of households measured in Tropical Livestock Unit (TLU) is also expected to influence consumption, poverty and vulnerability. In Ethiopia, livestock is an important source of capital during times of food shortage. It serves both as a source of liquid assets as well as a productive resource in the form of draft power. Therefore, building or having larger stocks of animals is considered to positively influence household consumption and thus reduce poverty and vulnerability. Land size measured in hectares is expected to influence consumption positively and help farmers to escape poverty or remain non-poor.

Demographic characteristics: Family size, the number of working household members, the dependency ratio and the educational status of the household head also influence poverty and vulnerability. Education represented by the number of years of formal schooling of the household head is hypothesized to have a positive effect on technology adoption and thus expected to influence consumption positively and reduce poverty and vulnerability. The age of the household head may have both positive and negative effects as it captures farming experience, attitudes towards new technologies and labor capacity. Gender represented by a dummy variable taking the value 1 if the household head is male and 0 for female headed households, expected to influence consumption. Male headed households are expected to have a higher level of consumption and lower poverty and vulnerability.

Experience of shocks: Smallholders in Ethiopia are prone to various types of shocks such as drought, flooding, pests and diseases which may be responsible for the perpetuation of poverty. Thus, household's experience of adverse shocks, the number of shocks reported[9] and the resulting amount of loss in monetary values are hypothesized to increase vulnerability to poverty. The amount of money spent on coping strategies may have both negative and positive effects. Since households may sell their assets or take credit to smooth consumption (Sharma et al., 2000), this may reduce poverty and vulnerability in the short run. However, the expense of the coping strategies decrease household's standard of living in the long run as they must repay loans or replace durable assets that were lost due to distress sale. Unlike the other explanatory variables mentioned above, only the last two rounds (2014 and 2016) have detailed information on self-reported shock experience by the sample households. Even though the households were asked to report their shock experience for the past three years in each survey round, it appears that almost all of them reported not have experienced any type of adverse shock in 2012.Therefore, we run a separate regression using the last two rounds controlling for households experience towards adverse shocks.

Off-farm income: Measured as a dummy variable taking a value of 1 if the household has at least one source of income other than farming is expected to influence consumption. Having other source of income may reduce financial constraints, particularly for poor farmers, enabling them to afford purchase the technologies. However, the net effect of off-farm income is a priori ambiguous, since participation in off-farm activities may restrict production in agriculture (Wozniak, 1984).

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[9] The different types of shocks reported were flooding, drought, illness of a family member as well as open grazing.

Region: The sample households are located in two regions (SNNP and Oromia), and we expect to see differences in the level of consumption as well as poverty and vulnerability in the two regions.

Table 2.1 presents the definitions and descriptive statistics of the variables included in the regression analysis using the pooled data of the three rounds. The mean of the continuous dependent variable (real per capita consumption expenditure) for the pooled data is ETB 412. The mean age of the household head is 47 and on average sample households have dependency ratio of 0.48. The technology choice sets as the main objective of this paper are expressed as dummy variables (see Table 2.1). On average, the combinations of the different technologies such as chemical fertilizer, improved seed and contour ploughing (50%); only chemical fertilizer (15%); chemical fertilizer, contour plough and pesticide (11%) are the most common technology choice sets observed in the sample farmers. The mean level of asset holdings as a measure of welfare which as well influences the level of household consumption, represented by the mean number of livestock owned (TLU) and land size in ha are 4 and 1.5, respectively. On average 50% of the sample households earn off-farm income. With regard to investment in irrigation, only 5% of the households use irrigation. Regarding the self-reported shock experience of sample households, only 7% of them reported to have experienced an adverse shock at least once between 2011 and 2016. The mean value of estimated loss due to shock is ETB 1345 and the mean expenditure on coping strategies against the adverse shocks reported is ETB 2728. SNNPR covers 64% of the sample households and the remaining 36% of the sample households are coming from Oromia region.

Table 2.1 Description of the variables in the regression models

Variables	**Mean**	**SD**
Real per capita consumption expenditure (ETB)	412	416
Poverty status (=1 if chronically poor, 2= vulnerable and 3=non-poor)	1.9	0.62
Gender (Dummy, =1 if the household head is male , 0 otherwise)	0.83	0.37
Household size (number of family members)	6.4	2.34
Age (age of the household head in years)	46.86	14.09
Dependency ratio (The ratio of non-working and working household members**)**	0.48	0.20
Land size (total farmland owned in ha)	1.5	1.5
Off-farm income (Dummy, 1=if the household earns off-farm income , 0 otherwise)	0.5	0.48
Irrigation (Dummy, 1=if the household irrigates at least one plot of land, 0 otherwise)	0.05	0.22
The square of age of household head	2395	1482
Livestock (the number of cows, sheep and goats measured in TLU)	4.16	4.69
Drought (Dummy, 1=if the household experienced any adverse shock, 0 otherwise)	0.07	0.25
Estimated loss due to shock (ETB)	1345	5190
Number of shocks reported per household	0 .29	0.62
Value of coping strategies (ETB)	2728	8988
Region (1= SNNPR, 0=Oromia)	0.64	0.48
$F_1V_0T_0C_0P_0$ (Dummy, 1=only chemical fertilizer)	0.11	0.3
$F_0V_1T_0C_0P_0$ (Dummy, 1=only improved seed)	0.03	0.17
$F_1V_0T_1C_0P_0$ (Dummy, 1=chemical fertilizer and improved seed)	0.02	0.17
$F_1V_0T_0C_1P_0$ (Dummy, 1=chemical fertilizer and contour plough)	0.06	0.24
$F_1V_0T_0C_0P_1$ (Dummy, 1=chemical fertilizer and pesticide)	0.06	0.25
$F_1V_1T_1C_0P_0$ (Dummy, 1= chemical fertilizer, improved seed, terraces)	0.03	0.16
$F_1V_1T_0C_1P_0$ (Dummy, chemical fertilizer, improved seed, contour plough)	0.5	0.2
$F_1V_1T_0C_0P_1$ (Dummy, chemical fertilizer, improved seed pesticide)	0.04	0.2
$F_1V_0T_1C_1P_0$ (Dummy, chemical fertilizer, terraces, contour plough)	0.02	0.15
$F_1V_0T_0C_1P_1$ (Dummy, chemical fertilizer, contour plough and pesticide)	0.15	0.3
$F_1V_1T_1C_1P_0$ (Dummy, chemical fertilizer, improved seed, terraces, contour plough)	0.03	0.17
$F_1V_0T_1C_1P_1$ (Dummy, chemical fertilizer, terraces, contour plough and pesticide)	0.03	0.17
$F_1V_1P_1T_1C_1$ (all the five technologies)	0.02	0.15
$F_1V_1T_0C_1P_1$ (four technologies except terracing)	0.04	0.2

Source: Pooled data - Ethiopia ATA Baseline (2012) Survey and DFG-Ethiopia – technology adoption survey (2014 and 2016). Attrition rate between 2014 and 2016 was 10/400=2.5%. F, V, T, C and P refer to chemical fertilizer, improved seed variety, terraces, contour plough, and pesticide; subscript '0' denotes non-adoption while '1'denotes adoption.

2.4 Results and Discussion

2.4.1 Poverty and Vulnerability Profile of Households

The primary focus of the study is to analyze the effect of PETs and SWC measures and their combinations on consumption, poverty and vulnerability. Real per capita consumption expenditure for food and other essential non-food items, such as clothing and footwear, is used as a proxy variable to measure poverty. Using the national poverty line in 2011 prices, sample households are grouped into poor and non-poor households, where the poor are those households whose consumption level is below the national poverty line and the non-poor are those households whose consumption level is above the national poverty line. The movement of sample households in and out of poverty between 2012 and 2016 is analyzed using a poverty transaction matrix presented in Table 2.2. Bold figures indicate the share of households that stayed in the same poverty category between two survey rounds. A visual inspection of the matrix show that household's poverty status is not stable over time. For instance, of the 290 poor households in 2012, only 46% and 28% remained poor in 2014 and 2016, respectively. Similarly, of the 100 non-poor households in 2012, 19% and 22% remained non-poor in 2014 and 2016, respectively.

Looking at the overall incidence of poverty in all of the three rounds of the data, we computed the headcount ratio that is the share of households living below the national poverty line, and the result shows that poverty has declined throughout the survey rounds. The 2012 headcount ratio was 70%; it fell to 50% and 30% in 2014 and 2016, respectively. This finding is consistent with other documentation on Ethiopia's progress in alleviating poverty and food insecurity (see World Bank, 2015). The World Bank report reveals that the rural poverty headcount ratio declined from 45.4% in 2000 to 30.4% in 2011. However, one can see that higher proportion of households entered poverty between 2014 and 2016 (8%) compared with 2012 and 2014 (6%). This suggests that the incidence of vulnerability to poverty is more prevalent than poverty itself, which was showed by other researchers like Haughton and Khandker (2009).

Table 2.2 Poverty transition matrix

Year		2014		2016	
		Poor	Non-Poor	Poor	Non-Poor
2012	Poor	**46**	29	**28**	47
	Non-Poor	6	**19**	3	**22**
2014	Poor			**23**	29
	Non-Poor			8	**40**

2.4.2 Differences in Household Characteristics by Poverty Status

The poverty grouping helps us to examine the differences between the poor and non-poor households in several demographic, economic, and institutional variables. These differences are provided in Table 2.3.

Table 2.3 indicates that female headed households tend to be poorer than male headed households throughout the survey rounds, though the proportion of poor households in both gender groups declined significantly. The descriptive results also show that non-poor households tend to have larger families throughout the survey rounds. Similarly, non-poor households have more household members who are economically active. This result suggests that non-poor households are better endowed with an economically active labor force. In both cases the mean difference between the two categories is significantly different at the 1% level of significance. However, the dependency ratio between poor and non-poor households is not significantly different for all three panel rounds. Regarding the education of the household head, the results show that in all rounds non-poor households have better educated heads than poor households at the 1% level of statistical significance, though the two groups of households are not statistically significantly different in terms of the age of their household head in 2012 and 2014.

With regard to consumption expenditure, there is no statistical difference in real per capita food consumption expenditure in all survey rounds. However, non-poor households have a statistically higher level of per capita consumption for other non-food items. Non-poor households also have higher per capita consumption for both food and non-food items in all three rounds at the 1% level of significance. Asset ownership in rural Ethiopia, such as ownership of livestock, is an integral part of smallholder farmers' production systems. Livestock provides manure and draft power for farm operations and serves as precautionary savings given imperfect financial markets. We find that non-poor households keep a significantly higher number of livestock than poor households. Concerning the differences in adoption of agricultural technologies, in the 2014 and 2016 survey rounds a significantly higher proportion of non-poor households used chemical fertilizer with no other complementary input. Similarly, there is a significant difference in the adoption of an improved variety; a higher proportion of non-poor households used an improved variety in 2012. However, the results show no significant difference in the use of chemical fertilizer in 2012 and an improved variety in 2014 and 2016. Likewise, a higher proportion of non-poor households use contour ploughing.

On the other hand, there is no evidence whether there is a statistical difference between the poor and non-poor in the use of terracing.

With regard to combinations of the technologies considered in the study, the descriptive results show poor households tend to adopt single technologies more frequently than the non-poor. For instance, a significantly higher proportion of poor households tend to adopt only chemical fertilizer and contour ploughing. Similarly, statistically significantly higher proportions of poor households are non-adopters (21%) compared with the non-poor (7.5%). On the other hand, there is a significant difference in the adoption of multiple technologies where a higher proportion of non-poor households tend to adopt multiple technologies compared with poor households.

With regard to information on experience to various shocks, households were asked to report if they had been affected by the different types of shocks in the past five years. Data on shock experience, however, was only collected in the 2014 and 2016 rounds. Therefore, we run a separate regression including the shock experience indicator variables as additional regressors using the two rounds of panel data (2014 and 2016). Our descriptive result shows that a higher proportion of poor households reported to be affected by the drought in 2016 compared with non-poor households. However, there was no difference in their experience of drought in 2014. On the contrary, in 2016, a significantly higher proportion of non-poor households experienced illness of a household member. With regard to households' experience of any type of shock between 2009 and 2016, we obtain mixed results for the two groups. In 2014, a higher proportion of non-poor households reported being affected by any shock than poor households (significant at 5%). The reverse holds true in 2016 when a higher proportion of poor households reported being affected by shocks relative to non-poor households (significant at 1%).

In summary, poor households own less livestock, have fewer economically active household members, a smaller family size with a female and less-educated household head. Compared with non-poor households, they also experience more adverse shocks and a lower rate of technology adoption.

Table 2.3 Differences in household characteristics by poverty status

Variables	2012			2014			2016		
	Poor	**Non-Poor**	**Sig.**	**Poor**	**Non-Poor**	**Sig.**	**Poor**	**Non-Poor**	**Sig.**
Female headed household	0.83	0.17	***	0.61	38	***	0.37	0.62	***
Male headed household	0.72	0.27	***	0.49	0.5	***	0.29	0.71	***
Family size	5.8	7.6	***	5.6	7	***	5.6	7	***
Mean number of working household members (aged 15 to 64)	2.8	3.8	***	2.8	3.6	***	2.5	3.6	***
Mean age of household head (years)	45	46		46	46		50	47	*
Mean dependency ratio	0.48	0.5		0.47	0.49		0.45	0.48	
Mean education of household head (years)	2.95	4.35	***	2.69	3.7	***	1.89	3.65	***
Mean value of food consumption expenditure per month (ETB)	287	333		481	545		353	394	
Mean value of monthly expenditure on essential items (ETB)	14	41	***	12	30	***	11	41	***
Mean value of real per capita consumption expenditure (ETB)	134	576	***	173	599	***	182	800	***
Mean number of loans taken over the past 12 months	0.45	0.32		0.17	0.21		0.24	0.4	
Mean number of livestock owned (TLU)	3	8	***	2	5.5	***	2	5	***
Households using irrigation (%)	2.31	2.31		1.79	2.82		1.03	4.87	
Households reported drought (%)	-	-		1.49	3.72		15	8.9	*
Households reported flood (%)	-	-		2.97	5.85		1.67	0	
Households reported illness (%)	-	-		5	4.38		3.59	4.36	*
Households experienced any type of shock (%)	-	-		24.26	34.04	**	30.00	17.78	***

Note: T-test used for continuous variables; χ^2-tests used for proportions; Mann-Whitney and rank-sum tests used for count variables.
*, **, *** indicate significant differences at α=0.10, α=0.05, α=0.01, respectively.

Table 2.3 Continued

Variable	2012			2014			2016			Pooled		
	Poor	Non-Poor	Sig.	Poor	Non-Poor	Sig.	Poor	Non-Poor	Sig.	Poor	Non-Poor	Sig.
PETs and SWC practices and their combinations (all are dummy, 1=adopted and 0 otherwise)												
$F_1V_0T_0C_0P_0$	84	88	*Na*	88	95	**	86	90	*na*	13.89	8.42	***
$F_1V_0T_0C_1P_0$	7.24	6	*Na*	7.43	6.38	*na*	5.83	4.81	*na*	7.03	5.56	*na*
$F_1V_0T_0C_0P_1$	9.31	6	*Na*	2.48	9.57	***	4.17	6.67	*na*	6.05	7.53	*na*
$F_1V_1T_0C_0P_1$	4.83	5	*Na*	4.46	8.51	*na*	0.83	2.96	*na*	3.92	5.2	*na*
$F_1V_0T_0C_1P_1$	9.66	12	*Na*	4.95	9.57	*	5	4.44	*na*	7.19	7.53	*na*
$F_0V_0T_0C_0P_0$	18.97	9	**	21.78	7.45	***	24.17	7.04	***	20.92	7.53	***

Note: χ^2-test is used for the comparison between the two groups and *, **, *** indicate significant differences at α=0.10, α=0.05, α=0.01, respectively. F, V, T, C and P refer to chemical fertilizer, improved seed variety, terraces, contour plough and pesticide; subscript '0' denotes non-adoption while '1' denotes adoption. The number of observations is 390 households for each round and 1170 for the pooled data.

The marginal and conditional probabilities of improved PETS and SWC measures are also presented in Table 2.4, which indicates complementarity among technologies; adoption of one technology improves the likelihood of adoption of the other technology. The adoption of improved seed variety, for instance, increases the adoption of chemical fertilizer and vice versa. Sometimes adoption of one technology may also decrease the likelihood of adoption of the other technology in cases of substitutability. The use of organic fertilizer for example may substitute the use of chemical fertilizer. As shown in the table below (Table 2.4), the probability of adopting chemical fertilizer when conditional on whether the household also adopted improved seed on average is greater than 85%. Likewise, adoption of chemical fertilizer increases the likelihood of adoption of the other four technologies. The most popular technology adopted in our sample households is chemical fertilizer followed by improved seed.

Table 2.4 Marginal and conditional probabilities of PETs and SWC adoption

	F=fertilizer			**V=improved seed**			**T=terracing**			**C=contour ploug.**			**P=pesticide**		
	2012	2014	2016	2012	2014	2016	2012	2014	2016	2012	2014	2016	2012	2014	2016
$P(A_M=1)$	0.66	0.71	0.76	0.34	0.37	0.41	0.40	0.26	0.28	0.34	0.40	0.50	0.36	0.33	0.29
$P(A_M=1\|A_F=1)$	1	1	1	0.71	0.88	0.93	0.81	0.82	0.89	0.78	0.83	0.85	0.83	0.96	0.96
$P(A_M=1\|A_V=1)$	0.37	0.0046	0.005	1	1	1	0.68	0.48	0.51	0.35	0.35	0.48	0.36	0.45	0.42
$P(A_M=1\|A_T=1)$	0.05	0.003	0.003	0.80	0.34	0.35	1	1	1	0.005	0.36	0.40	0.07	0.25	0.34
$P(A_M=1\|A_C=1)$	0.40	0.0047	0.0056	0.34	0.38	0.59	0.43	0.55	0.72	1	1	1	0.46	0.54	0.69
$P(A_M=1\|A_P=1)$	0.45	0.0044	0.0037	0.37	0.39	0.30	0.68	0.31	0.35	0.49	0.44	0.41	1	1	1
$P(A_M=1\|A_F=1\&A_V=1)$	1	1	1	1	1	1	1	0.35	0.36	0.37	0.40	0.61	0.43	0.45	0.32
$P(A_M=1\|A_F=1\&A_T=1)$	1	1	1	0.76	0.53	0.55	1	1	1	0.46	0.61	0.75	0.76	0.38	0.39
$P(A_M=1\|A_F=1\&A_C=1)$	1	1	1	0.34	0.39	0.54	0.055	0.40	0.44	1	1	1	0.58	0.51	0.47
$P(A_M=1\|A_F=1\&A_T=1\&A_C=1)$	1	1	1	0.66	1	0.48	1	1	1	1	1	1	0.83	0.47	0.50
$P(A_M=1\|A_v=1\&A_T=1\&A_C=1)$	0.80	0.93	0.95	1	1	1	1	1	1	1	1	1	0.60	0.41	0.39

Note: Subscripts M, F, V, T, C and P represent type of technology, chemical fertilizer, improved variety, terracing and contour ploughing, respectively.

2.4.3 Econometric Results

Using per capita consumption expenditure as a dependent variable, we estimated a two-stage endogenous switching regression multinomial logit (ESMNL) regression model to analyze the impact of technologies on consumption. Following the Mundlak approach, we also run a random effects model and the results are qualitatively similar to those of the ESMNL regression model. Our results support the presence of both time varying and time-invariant unobserved heterogeneity that affect both technology set choices and outcome variables (consumption expenditure and poverty profile), emphasizing the importance of controlling selection bias in evaluating technology sets. The outcome regression equation results are presented in Table 2.5 and Table 2.6.

Table 2.5 shows the expected actual, counter factual and average treatment effect (ATT) on adopters. The ATT is the difference between the expected actual value of consumption and the counterfactual outcome. The ATT results show that all the technology sets, except the category for minor combinations, have positive and significant impacts on consumption expenditure. The difference to the log values can be converted to percentages and the results indicate that adopting only chemical fertilizer with no other complementary input significantly increases consumption by 15%. On the other hand, combining chemical fertilizer with contour ploughing significantly increases consumption by 1%. The unexpected result, that complementing chemical fertilizer with contour ploughing has lesser consumption effects, could be because our measure of adoption does not consider the intensity of adoption. Similarly, the joint adoption of chemical fertilizer and pesticide increases consumption by 15%. The adoption of the three technologies (chemical fertilizer, improved seed and pesticide) significantly increases consumption expenditure by 16%. In summary, the results show that the adoption of multiple technologies increases consumption. In our case, the highest impact is observed when at least three of the technologies considered here are adopted together. Recent empirical evidence by Kassie et al. (2015, 2018), Manda et al. (2016), and Teklewold et al. (2013) in Ethiopia and elsewhere also demonstrate that a combination of technologies provide higher net returns than when only a single technology is adopted.

Table 2.5 The expected actual and counterfactual consumption estimates and the average treatment effect (ATT) on adopters

Set of technologies	**Actual observed consumption**	**Counterfactual (consumption if a household did not adopt)**	**ATT**	**Sig**
$F_1V_0T_0C_0P_0$	5.1	4.44	0.66	**
$F_1V_0T_0C_1P_1$	5.72	5.65	0.07	*
$F_1V_0T_0C_0P_1$	5.7	4.96	0.74	**
$F_1V_1T_0C_0P_1$	5.8	5	0.8	**
$F_1V_1T_1$,$F_1T_1C_1$, $F_1V_1T_1C_1P_1$,$F_1V_1C_1$, $F_1V_1T_1C_1$, $F_1T_1C_1P_1$[10b]	6.06	6.05	0.01	**
V_1, F_1T_1 and F_1C_1[11]	5.5	4.7	0.8	*

[a]F,V,T,C and P denotes chemical , improved seed, terraces, contour plough and pesticide, respectively.
[b] $F_1V_1T_1$, $F_1T_1C_1$, $F_1V_1T_1C_1P_1$, $F_1V_1C_1$, $F_1V_1T_1C_1$, and $F_1T_1C_1P_1$ were merged because of insufficient observations for separate regressions.

The random effects model estimation using the Mundlak approach is presented in Table2. 6. The random effects estimates support the outcomes observed in Table 2.6, which are obtained by using separate regressions for each practice and the results are qualitatively similar. The adoption of technologies considered in this study (chemical fertilizer, improved seed, terracing and contour plough) and their combinations have the anticipated effect and are found to be positively associated with consumption. The adoption of chemical fertilizer and improved seed each with no other complementary input increases consumption by 17% and 40%, respectively. Overall, most of the technology sets included in the model appear to have a positive and statistically significant impact on consumption, as expected. The model result also reveals that the highest impact of adoption is observed for the technology combination chemical fertilizer and improved seed combined with at least one of the SWC practices, which increases consumption by more than 60%.

Regarding household demographics, the gender of the household head is negatively associated with consumption. It is shown that male headed households have 15% less consumption than female headed households. However, the poverty classification shows that female headed

[10] Included are $F_1V_1T_1$, $F_1T_1C_1$, $F_1V_1T_1C_1P_1$, $F_1V_1C_1$, $F_1V_1T_1C_1$, and $F_1T_1C_1P_1$. The subscript '0' for non-adoption is missing to save space for the remaining technologies

[11] Included are V_1, F_1T_1, and F_1C_1. We combine these practices because there are no adequate observations to run separate regressions for each practice. The subscript '0' for non-adoption is missing to save space for the remaining technologies

households are poorer with fewer assets. In this analysis, the food consumption calculation is based on the seven-day recall approach and women headed households may spend more on food than investment goods contrary to male headed households. Household size represented by the number of family members is positively associated with consumption over time. An additional household member significantly increases real consumption per capita by more than 12%. This positive effect is similar to the findings of Demeke et al. (2011) in Ethiopia, suggesting household size when controlling for dependency ratio influences food security positively. The age of the household head and the number of livestock are not significant factors of consumption in this model. Farm size has a positive and significant effect on both models. Though weakly significant, income other than farming has a positive impact on consumption in the second model. To control for spatial effects, the region dummy was included in the model. As expected, the estimates show that households located in SNNPR have about 23% less consumption than those in Oromia region. Time dummies were also significant and show an increase in consumption over time. The random effects model results also suggest that money spent on coping strategies is positively associated with consumption.

Table 2.6 Random effects coefficients using the Mundlak approach and panel data

Explanatory[12] variables	Random effects model coefficients					
Gender of head(1=Male, 0=Female)	-0.07		(0.06)	-0.15	**	(0.07)
Education of HH head	0.0398	***	(0.01)	0.03	***	(0.01)
Age of HH head	0.01		(0.011)	0.003		(0.01)
Dependency ratio	-0.505	***	(0.14)	-0.61	***	(0.145)
Land size (ha)	0.102	***	(0.02)	0.08	***	(0.03)
Square of age	-0.0001		(0.0001)	-0.000		(0.0001)
Off-farm income (1=yes, 0=no)	0.0710		(0.05)	0.10	*	(0.054)
Household size (number of family members)	0.127	***	(0.014)	0.133	***	(0.015)
Number of livestock owned (TLU)	0.000		(0.000)	0.000		(0.000)
PETs and SWC practices and their combination						
$F_1V_0T_0C_0P_0$	0.172	*	(0.09)	0.25	**	(0.111)
$F_0V_1T_0C_0P_0$	0.409	***	(0.145)	0.186		(0.146)
$F_1V_0T_1C_0P_0$	0.485	***	(0.116)	0.6	***	(0.123)
$F_1V_0T_0C_1P_0$	0.245	**	(0.102)	0.38	***	(0.130)
$F_1V_0T_0C_0P_1$	0.441	***	(0.110)	0.60	***	(0.123)
$F_1V_1T_1C_0P_0$	0.329	***	(0.121)	0.46	***	(0.125)
$F_1V_1T_0C_1P_0$	0.620	***	(0.103)	0.64	***	(0.113)
$F_1V_1T_0C_0P_1$	0.482	***	(0.095)	0.62	***	(0.105)
$F_1V_0T_1C_1P_0$	0.650	***	(0.151)	0.67	***	(0.149)
$F_1V_0T_0C_1P_1$	0.388	***	(0.083)	0.48	***	(0.1)
$F_1V_1T_1C_1P_0$	0.541	***	(0.107)	0.68	***	(0.115)
$F_1V_0T_1C_1P_1$	0.306	**	(0.137)	0.46	***	(0.155)
$F_1V_1P_1T_1C_1$	0.540	***	(0.101)	0.63	***	(0.110)
$F_1V_1T_0C_1P_1$	0.472	***	(0.113)	0.66	***	(0.111)
Region (1=SNNP, 0==Oromia)	-0.237	***	(0.062)			
2014	0.559	***	(0.05)			
2016	0.95	***	(0.054)	0.43	***	(0.05)
Number of shocks				-0.05	***	(0.015)
Estimated loss due to shock				-0.0001	***	(0.000)
Estimated value of coping strategy				0.0001	***	(0.000)
N	**1,170**					**780**
Pro > chi2	**0000**					**0000**
R2 overall	**0.48**					**0.42**

* Robust standard errors are given in Parentheses. *, **, *** indicate significant differences at α=0.10, α=0.05, α=0.01, respectively. *The dependent variable is the natural log of real consumption expenditure.*

[12] The coefficient for irrigation that was included in the model is not significantly different from zero. The coefficients for the mean of the time varying predictor variables and the mean of the inverse Mills ratio were also not significantly different from zero.

To analyze the impact of adoption of single technologies and their possible combinations on the different poverty categories, an ordered probit model is employed using the 2012 baseline data. The model's marginal effects estimates are presented in Table 2.7. The results show that the adoption of single technologies or their combinations have the expected signs and support the previous counterfactual and random effects model analysis. Most of the technology set variables included in the model are significant and have the expected signs. The adoptions of the single technologies or their combinations reduces the likelihood of households being in the chronically poor situation or enable them to move to a better welfare situation, in this case the vulnerable and non-poor categories.

Regarding the demographic characteristics, household size and education of the household head influences the likelihood of households being in the different poverty categories. The variable household size has the anticipated sign. Households with more family members are likely to escape the chronically poor category. An additional family member in the household decreases the likelihood of the household being chronically poor by 4.8%. The gender and age of the household head appear not to be significant factors in this model. In line with the hypothesis, the number of livestock and other sources of income significantly improve the poverty status of households. The regional dummy variable estimate shows that households located SNNPR are less likely to escape poverty than those in Oromia.

Overall, both the random effects and OP model results indicate that there is a strong link between agricultural technology and consumption, poverty, and vulnerability.

Table 2.7 Ordered probit model marginal effects

Explanatory Variables	Ordered Probit Model (Marginal Effects)								
	Chronically Poor			Vulnerable			Non-Poor		
Gender	0.05		(0.04)	-0.005		(0.009)	0.01		(0.004)
Education of HH head	-0.14	***	(0.005)	0.002	*	(0.002)	0.01	***	(0.04)
Household size	-0.048	***	(0.008)	0.01	**	(0.004)	0.04	***	(0.006)
Age of household head	-0.001		(0.006)	0.0002		(0.001)	0.0009		(0.005)
Farm size (ha)	0.005		(0.15)	-0.001		(0.003)	-0.004		(0.12)
Other Income	-0.09	***	(0.03)	0.017	*	(0.009)	0.07	***	(0.024)
Number of livestock (TLU)	-0.017	***	(0.008)	0.01	*	(0.002)	0.014	***	(0.004)
Region (SNNPR=1, Oromia=0)	0.1	**	(0.039)	-0.02	*	(0.011)	-0.08	**	(0.031)
Age square	0.000		(0.000)	-0.000		(.0001)	-0.0001		(0.000)
$F_1V_0T_0C_0P_0$	0.120	***	0.03	0.77	***	(0.03)	0.10	**	(0.031)
$F_0V_1T_0C_0P_0$	0.048	*	0.025	0.71	***	(0.077)	0.24	**	(0.09)
$F_1V_0T_1C_0P_0$	0.202		0.36	0.74	***	(0.23)	0.06		(0.13)
$F_1V_0T_0C_1P_0$	0.19	***	0.068	0.74	***	0.048)	0.064	**	(0.027)
$F_1V_0T_0C_0P_1$	0.14	***	0.04	0.76	***	(0.03)	0.092	***	(0.034)

Table 2.7 continued

Explanatory Variables	Ordered Probit Model (Marginal Effects)								
	Chronically Poor			Vulnerable			Non-Poor		
$F_1V_1T_1C_0P_0$	0.13		(0.17)	0 .76	***	(0.047)	0.09		0.14
$F_1V_1T_0C_1P_0$	0.04	*	(0.02)	0.6	***	(0.092)	0.28	**	0.11
$F_1V_1T_0C_0P_1$	093	**	(0.04)	0 .76	***	(0.03)	0.14	**	0.06
$F_1V_0T_0C_1P_1$	0.10	***	(0.026)	0.76	***	(0.027)	0.13	***	0.31
$F_1V_1T_1C_1P_0$	0.035		(0.07)	0.64		(0.41)	0.12		0.19
$F_1V_0T_1C_1P_1$	0.107		(0.17)	0.76	***	(0.034)	0.05		0.067
$F_1V_1P_1T_1C_1$	0.21		(0.20)	0 .72	***	0.13)	0.192		0.087
$F_1V_1T_0C_1P_1$	0.06	*	(0.03)	0.74	***	(0.57)	0.089	**	0.034
Prob > chi2	0.0000								
LR chi2 (26)	166								
Psuedo R-square	0.22								
N	390								

*Robust standard errors are given in Parentheses. *, **, *** indicate significant differences at α=0.10, α=0.05, α=0.01, respectively. DP variable for the OL model is poverty status (1= Chronically poor, 2=vulnerable and 3=non-poor).

2.5 Conclusion and Recommendations

The main objective of this paper is to estimate the impact of agricultural technologies, particularly PETs (chemical fertilizer, pesticide and improved seed) and SWC practices (terraces and contour ploughing) and their possible combinations, on consumption, poverty and vulnerability. The analysis is based on three rounds of balanced household panel data collected in 2012, 2014, and 2016, with a sample size of 390 households. We estimated an endogenous switching multinomial logit model combined with panel data following the Mundlak approach and, assuming a different slope coefficient, we ran seven separate regressions for the different technology combinations. From this regression the expected counterfactual outcomes for the adopters were calculated. Alternatively, following the same approach, we estimated the random effects model while controlling for unobserved heterogeneity. The impact of the technologies on the three poverty categories (chronically poor, vulnerable and non-poor) was also analyzed using the ordered probit model.

The descriptive results reveal that poor households own less livestock and have fewer economically active household members, a smaller family size and a less-educated household head. They also experienced more adverse shocks, spent less on chemical fertilizer, and used improved varieties and pesticides less frequently. The econometric modeling results suggest that PETs and SWC measures and their combinations contribute to the reduction of poverty and vulnerability and improve consumption over time. The highest impacts of technologies are observed when these technologies are adopted jointly. We found that the use of combinations of chemical fertilizer, improved seed variety, pesticide and SWC practices lead to higher levels of real per capita consumption. The ordered probit marginal effects estimates also supported the counterfactual analysis and show that agricultural technologies are crucial to reducing poverty.

Based on our findings, we conclude that the adoption of PETs and SWC measures are very helpful in improving the welfare of adopters irrespective of their poverty status (chronically poor, vulnerable, or non-poor). We, therefore, suggest that much more intervention is warranted to ensure that the chronically poor and vulnerable farm households can have access to improved agricultural technology.

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Appendix

Table A1 Differences in household characteristics by poverty status

Variable	2012			2014			2016			Pooled		
	Poor	Non-Poor	Sig.	Poor	Non-Poor	Sig.	Poor	Non-Poor	Sig.	Poor	Non-Poor	Sig.
PETs and SWC practices and their combinations (all are dummy, 1=adopted and 0 otherwise)												
$F_1V_0T_0C_0P_0$	84	88	*Na*	88	95	**	86	90	*na*	13.89	8.42	***
$F_0V_1T_0C_0P_0$	3.45	10	***	3.96	1.6	*na*	1.67	1.48	*na*	3.27	3.05	*na*
$F_0V_0T_1C_0P_0$	0.34	0	*Na*	3.47	2.13	*na*	1.67	1.48	*na*	1.63	1.43	*na*
$F_0F_0T_0C_1P_0$	4.48	2	*Na*	6.44	2.66	*	8.33	3.7	*	5.88	3.05	**
$F_1V_0T_1C_0P_0$	0	0		2.97	2.66	*na*	0.83	1.85	*na*	1.14	1.79	*na*
$F_1V_0T_0C_1P_0$	7.24	6	*Na*	7.43	6.38	*na*	5.83	4.81	*na*	7.03	5.56	*na*
$F_1V_0T_0C_0P_1$	9.31	6	*Na*	2.48	9.57	***	4.17	6.67	*na*	6.05	7.53	*na*
$F_1V_1T_1C_0P_0$	0.69	0	*Na*	2.48	4.79	*na*	5.83	4.07	*na*	2.29	3.58	*na*
$F_1V_1T_0C_1P_0$	2.76	8	**	1.49	3.19	*na*	4.17	10.37	*na*	2.61	7.53	***
$F_1V_1T_0C_0P_1$	4.83	5	*Na*	4.46	8.51	*na*	0.83	2.96	*na*	3.92	5.2	*na*
$F_1V_0T_1C_1P_0$	0	0	*Na*	3.47	3.19	*na*	5	3.7	*na*	2.12	2.87	*na*
$F_1V_0T_0C_1P_1$	9.66	12	*Na*	4.95	9.57	*	5	4.44	*na*	7.19	7.53	*na*
$F_1V_1T_1C_1P_0$	0.34	0		3.96	3.72	*na*	0.83	7.41	***	1.63	4.84	***
$F_1V_0T_1C_1P_1$	0.34	1	*Na*	1.98	4.79	*na*	3.33	7.04	*na*	1.47	5.2	***
$F_1V_1P_1T_1C_1$	1.03	0	*Na*	1.49	4.79	*	2.5	4.44	*na*	1.47	3.76	**
$F_1V_1T_0C_1P_1$	4.14	4		2.97	5.32	**	2.5	7.41	*	3.43	6.09	**
$F_0V_0T_0C_0P_0$	18.97	9	**	21.78	7.45	***	24.17	7.04	***	20.92	7.53	***

Note: χ^2-test is used for the comparison between the two groups and *, **, *** indicate significant differences at α=0.10, α=0.05, α=0.01, respectively. F, V, T, C and P refer to chemical fertilizer, improved seed variety, terraces, contour plough and pesticide; subscript '0' denotes non-adoption while '1' denotes adoption. The number of observations is 390 households for each round and 1170 for the pooled data.

Table A2 Traditional Agro-climatic Zones and their physical characteristics

Zone	Altitude (m)	Rainfall (mm/year)	Length of Growing Period (d)	Average Annual Temperature (°C)
Wurch (cold and moist)	3200 plus	900–2200	211–365	>11.5
Dega (cool and humid)	2300–3200	900–1200	121–210	17.5/16.0–11.5
Weyna Dega (cool sub-humid)	1500–2300/2400	800–1200	91–120	20.0–17.5/16.0
Kolla (warm semi-arid)	500–1500/1800	200–800	46–90	27.5–20
Berha (hot arid)	under 500	under 200	0–45	>27.5

Chapter Three

3. The Impact of Agricultural Technologies on Crop Yields of Smallholders in Ethiopia: A Panel Data Analysis

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Abstract

Smallholders commonly apply different interrelated agricultural technologies to produce a mix of crops. Past research has mainly focused on analyzing the link between single technology adoption and single crop. Literature that directly addresses the impact of packages of technologies on the yield of multiple crops is scarce. This study investigates the impact of multiple technology adoption on the yield of Ethiopia's dominant staple crops namely teff, maize, wheat, and barley using four rounds of panel data collected in 2012, 2014, 2016, and 2019. By applying a multinomial endogenous switching regression model, we have also attempted to ease the issues of unobserved heterogeneity of farmers and self-selection bias of technology adoption The results reveal that, on average, adopters, in general, have higher yield gain compared with the non-adopters and highest yields gains are achieved when smallholders complement chemical fertilizer with the improved variety and soil and water conservation practices compared with single technology adopters. We find that compared with non-adopters, adopters have 44%, 56%, and 69% higher yield gains in teff, barley, and wheat, respectively. Factors such as the age of the household head, household demography, farm size, agro-ecological zone, and remoteness of the household appear to be significant determinants of crop yield. We conclude that more publicly funded efforts could be worthwhile for easing adoption constraints, which would in turn help smallholders increase their crop yields and thereby improve rural livelihoods.

Keywords: Ethiopia; panel data; crop yield; productivity; technology adoption

3.1 Introduction

The vast majority of households in Ethiopia are smallholder farmers that are primarily dependent on subsistence, rain-fed agriculture for their livelihoods (CIA, 2015; World Bank, 2005). Smallholders account for more than 95% of agricultural production and more than 85% of employment in the country (Dessale, 2019). Smallholders' livelihoods have been frequently threatened by weather extremes, such as recurrent drought, erratic rainfall, water shortages, and increased incidences of pests and diseases. Such events mainly lead to a decline in crop yields or, in some cases, total crop failure (Beegle et al., 2016). The negative effect of these external factors is further exacerbated by the fact that farmers apply minimum level of improved inputs and declining soil fertility.

Consequently, seasonal food shortages due to low production are a common phenomenon among smallholder farmers in the country. Low levels of improved agricultural input use and declining soil fertility further decrease farmers' ability to adapt to these risks. For instance, between 2014 and 2017, Ethiopia had an average food supply of 47.5 (kcal/capita/day)[13] from all food sources that could be consumed (FAOSTAT, 2020) which ranked the country 100th out of 173 countries. Other factors reported to be contributing to the low level of crop yield include credit and factor market failures, the weak market for agricultural commodities, as well as several other socio-economic factors (Abebe and Sewnet, 2014; Asfaw et al., 2011; Doss and Morris, 2000; Misiko and Ramisch, 2007; Pender et al., 2006; World Bank, 2005).

The critical roles played by agricultural, productivity-improving technologies, and soil and water conserving practices on the livelihoods of the poor have been acknowledged for many years. Ethiopia's government and other concerned parties have been promoting the use of packages of agricultural technologies in Ethiopia that are considered the main pathways for rural households to escape poverty (Christiaensen et al. 2011; Collier and Dercon 2014; Jayne and Rashid 2013; MoFED, 2010). Due to the scarcity of arable land and the associated environmental and social costs, an increase in agricultural production through area expansion of cultivated land is highly unlikely in Ethiopia. The large-scale public investment and promotion of agricultural technology packages by the government helped smallholders to adopt suitable new agricultural technologies (Jayne and Rashid, 2013; Rashid et al., 2013). Specifically, agricultural research and technological improvement centers in the country have

[13] This is own calculation using FAOSTAT data.

been focusing on improving the management and the production of crops, livestock, and natural resource systems.

Since 1994, the Agricultural Development Lead Industrialization (ADLI) functioning as the main national development framework, Ethiopia has implemented several sucesssive national development plans including the SDPRP (2002-2005), PASDEP (2005-2010), GTPI (2010-2015), and the current GTPII (2015-2020) with a common national objective of improving agricultural productivity and food security in the country (Howard et al., 2003; MoFED, 2010; MoFED, 2003; OECD, 2018). To date, however, smallholders show limited productivity growth and the agricultural sector is quite stagnant. Among the many contributing factors, evidences show the low level and/or incomplete adoption and mismanagement of agricultural technology packages to be the most important factor (Abate et al., 2018). Ethiopian smallholders show a considerably larger productivity gap in the production of different cereal crops than most developing countries and even lower yield compared with other sub-Saharan African (SSA) countries (World Bank, 2007b; Foster and Rosenzweig, 2010).

In investigating the impact of improved technologies adoption, past studies have usually focused on a single output versus single input, assuming that input allocation decisions are separable and can be made independently of output allocation decisions (Ali and Abdulai, 2010; Julio and German, 2001; Thirtle et al., 2001; Zeng et al., 2015) mainly due to the fact that multiple input versus multiple outputs is problematic for estimation. However, there are quite a number of studies that analyzed the combined effects of different technologies on yield. These studies, however, mainly used cross-sectional data (Abate et al., 2018; Abdulai and Huffman, 2014) that fails to capture the dynamic effects of adoption. On the contrary, studies on the impact of the adoption of different complementary technologies on yield is scarce (Kassie et al., 2018). To fill this research gap, we use four rounds of unbalanced panel data to analyze the impact of the different combinations of productivity-enhancing technologies (PETs) and soil and water conservation (SWC) techniques, on the yield of Ethiopia's key crops namely teff, maize, wheat, and barley.

The PETs included in this study are chemical fertilizer, high yielding variety (HYV), pesticide and/or herbicide, and the SWC techniques are terracing and contour ploughing. In a conventional rain-fed production system, smallholders apply multiple complementary inputs to produce several agricultural outputs. This situation is typical for Ethiopian smallholders that necessitate the importance of a comprehensive assessment of to what extent the technologies impact the different crop yields at the household level as the impact analysis based on a single technology and single output adoption may not provide a clear picture. There are always interaction effects of the complementary technologies as well as a trade-off on the use of inputs on the different outputs. The two-stage Multinomial Endogenous Switching Regression (MESR) model combined with the Mundlak approach is employed to assess the impact of the five technology combinations on the yield of Ethiopia's dominant crops namely, teff, maize, wheat, and barley. This study enables us to derive policy recommendations aimed at relaxing the adoption constraints of both productivity-enhancing and resource-conserving innovations that allow households to cope with increasing climate and price volatilities and escape risk-induced poverty traps.

3.2 Background

Besides the prevalence of rural poverty and food insecurity at the household and individual levels, the issue of national food supply versus demand remains a challenge in Ethiopia. Over the past decades, rapid population growth, urbanization, and an increase in incomes have led to a significant increase in the demand for food. Such an increase in food demand has negative impacts on smallholders who are mainly net buyers of food (Dercon et al., 2005). Responding to the growing food demand and at the same time eradicating poverty and food insecurity through the expansion of cultivated land is not a viable avenue in Ethiopia as arable land is a scarce resource and there are high environmental costs associated with agricultural land expansion (Assefa et al., 2020). A more promising option is to increase agricultural productivity using improved technologies. In this regard, economic growth and development programs in the country place more emphasis on cereals. While Ethiopia's crop yields have improved over the past decades, they remain relatively low compared with other developing . The average national yields of the staple crops considered in this paper, that is teff, barley, wheat, and maize, were 1.86, 2.54, 2.98, and 4.24 tons/ha, respectively (CSA, 2020). The potential yield of those crops is estimated to be at least twice higher than the actual yield much higher than the actual reported yield (MoARD, 2008). The most important factor that lead to this huge yield gap is attributed to the low rate of use of improved inputs (source). This is why governments in developing countries in general and Ethiopia in particular prioritized smallholders' use of sustainable improved agricultural technologies. The adoption of sustainable improved agricultural technologies were seen as a central component of the agricultural development strategies for increasing national food production and thereby food security in Ethiopia.This large yield gap in staple cereal crops is mainly attributed to the limited agricultural technology adoption and this has been directly linked to seasonal food shortages among smallholder producers in particular and low marketable surplus to other consumers (Abate et al., 2015). Therefore, narrowing the difference between the potential and the actual yield gaps at the farmers' level through the use of sustainable improved agricultural technologies is seen as a central component of the strategies for increasing food production and thereby food security in Ethiopia.

Thus, the limited access to improved productivity enhancing agronomic practices as well as low soil fertility improvement coupled with a lack of credit market are some of the main factors hindering crop yield growth. Therefore, the country's development strategies have given much emphasis on smallholder agriculture where considerable resources have been devoted to the development and dissemination of agricultural technologies. However, the level of smallholders' technology adoption and thus impact on the livelihoods of the poor remained very low (Biru et al., 2020; Kassie et al., 2018; Spielman et al., 2011; World Bank, 2007b). In this study, we considered the crop yield of the main harvest season (Meher season), which has harvests between September and February. Some pertinent specifics regarding the production of the four crops are presented below.

Wheat is typically grown by smallholders in Ethiopia's highlands and is an important component of Ethiopia's production system. Recent estimates show that wheat farmers in Ethiopia produce 2.9 tons/ha on average, well below the experimental yield of above 5 tons/ha (CSA, 2020) and below the average yield in Africa. According to the FAO (2014), in 2012, Ethiopia's wheat yields were on average 29% below Kenya's, 13% below the African average, and 32% below the world average. Maize is the largest and most productive crop in Ethiopia and elsewhere. In the 2012/2013 season, maize production was 4.3 million tons, which was 40% higher than teff, 56% higher than sorghum, and 75% higher than wheat production. With an average yield of 3.1 tons/ha from 2008 to 2019, maize has been the leading cereal crop in Ethiopia since the mid-1990s in terms of both crop yield and production. Wheat and sorghum yields have both averaged 2.1 tons/ha (CSA, 2019).

Teff is one of the most important and dominant staple cereal crops in Ethiopia (Lee, 2018) . Though teff is a relatively researched cereal crop, it is the second-largest cereal crop in terms of total production with an average yield of 1.6 tons/ha (CSA, 2020). According to the CSA figures, teff accounted for approximately 28% of the total cereal crop cultivated area and 50% of the total cereal production quantity.

Barley is a major crop across the highlands of Ethiopia. The country is one of the major producers of barley in SSA and has a growing malt beverage sector. According to CSA (2020), the average barley yield in the 2019 Meher season was 1.8 tons/ha. The new HYV introduced by the research centers in Ethiopia generates up to 4.1 tons/ha.

3.3 Methodology

3.3.1 Data and Study Area

The analysis is based on four rounds of household-level panel data collected in a random sample of 400 farm households from 29 kebeles selected in fifteen districts (woredas) of Southwestern Ethiopia, each differing in their climatic and agro-ecological characteristics. The households were selected using a stratified random sampling procedure (Minot and Sawyer, 2013; Spielman et al., 2011). The follow-up surveys conducted in 2014, 2016, and 2019 were limited to those baseline households living in Oromia Region and Southern Nations, Nationalities, and Peoples' Region (SNNPR). Those farmers who produced at least one crop out of the four crops (teff, maize, wheat, and barley) in at least one of the four rounds are considered in the analysis of this paper.

In Ethiopia, there are two rainy seasons: meher and belg, and consequently, there are two crop seasons. Meher encompasses crops harvested between Meskerem (September) and Yeaktit (February). It is the main production season; in 2012, for instance, over 97% of total crop production and 95% of total cereal production were in meher season. Crops harvested between March and August are considered part of the belg season. Due to the small proportion of producers during the belg season, we only considered the meher production data for our analysis.

Our data was collected between June and September for the 2012 survey round and between March and June for the last two rounds. Using the pooled data, about 246, 618, 487, and 640 households produced at least teff, maize, wheat, and barley, respectively. Data collection was carried out by a fieldwork team consisting of eight well-trained enumerators, two supervisors, and a fieldwork coordinator. During the planning and initial phase of the 2014, 2016, and 2019 rounds, experts from IFPRI, the University of Hohenheim, and private consultants supported the programming of computer-assisted personal interviewing (CAPI) devices, training of enumerators, and pre-testing of the questionnaire. Using CAPI ensured superior quality data through built-in consistency checks and other correction methods. The main parts of the questionnaire include demography, asset ownership, technology, input use, consumption, production, health, risk, and ambiguity.

3.3.2 Description of Explanatory Variables

Our prior expectations regarding the underlying links between the explanatory varianles included in the regression models and crop yield of Ethiopia's smallholders is explained below.

The demographic characteristics that are hypothesized to influence crop productivity are household size, number of economically active household members, age of the household head, dependency ratio, and education of the household head. Household size may have both positive and negative effects depending on the proportion of economically active household members . The number of working household members is expected to influence crop productivity positively. Education represented by the number of years of formal schooling of the household head is expected to have a positive effect on technology adoption and thus influence productivity positively. The age of the household head may have both positive and negative effects as it captures the farming experience of the household head, attitudes towards new technologies, and labor capacity. Gender, represented by a dummy variable taking the value 1 if the household head is male and 0 female, is expected to influence productivity as well. Male-headed households are expected to be more productive than female-headed households due to several cultural or socio-economic factors that disadvantage women.

The wealth of the household, represented by the number of livestock owned in tropical livestock units (TLU) and farm size (ha), is hypothesized to influence crop productivity. In Ethiopia, livestock is an important source of capital during times of food shortage. It serves both as a source of liquid assets (for instance to buy operational inputs) as well as a productive resource in the form of draft power. Therefore, raising larger stocks of animals is considered to positively influence productivity through soil fertility (manure) as well as draft power. Farm size, measured in hectares, is expected to be associated with crop productivity both positively and negatively. Evidence suggests that land size is negatively associated with productivity in the case of large holders and positive in the case of smallholders. Since farmers in our study area are all smallholders (the average farm size is less than 2 ha), farm size is hypothesized to be positively associated with productivity because cultivating relatively more land that is enough to accommodate family labor, is expected to increase crop productivity.

The household's access to infrastructure and services is represented by the distance of the household from the nearest periodic markets and agricultural research centers, as well as by the number of agricultural extension visits received. In Ethiopia, gains from yield and thereby, poverty and food insecurity, are strongly associated with geographic and location-specific variables of the household. Rural households living far from towns are less likely to access improved inputs, such as chemical fertilizer, and are less likely to benefit from gains in agricultural growth. The number of agricultural extension visits received by the household is also expected to impact crop productivity. Agricultural extension agents in Ethiopia provide technical assistance with the use of improved technologies and serve as a source of information, which may lead to improved crop production and productivity. Extension services also help farmers to collaborate with other smallholders and connect with agribusinesses and agricultural research centers, which further improves their gains from yield and thereby efficiency. The different agro-ecological zones of the study area are also included in the regression model and are expected to affect crop yield. The benefits that smallholders experience from different yield enhancing technologies vary by agro-ecological zone.

Smallholders in Ethiopia are prone to various shocks, such as drought, flooding, pests, and diseases that may be responsible for the perpetuation of poverty and limited crop productivity. Adverse shocks, represented by a dummy variable equal to 1 if the household experienced any type of adverse shock in the past five years and 0 if otherwise, were hypothesized to decrease crop productivity. The adverse shocks reported by the sample households included drought, flooding, death of a family member, political unrest, and other types of community- or household-level shocks that cause a substantial loss of welfare and a related reduction in the use of agricultural inputs and technology.

Five agricultural technologies (chemical fertilizer, HYV, pesticide and/or herbicide, terracing, and contour ploughing) and their possible combinations are represented as dummy variables taking the value of 1 if the household applied the technology to any of its crops and 0 if otherwise (see Table 3.2). These technologies are expected to be positively associated with crop yield, given favorable weather. These technologies increase crop productivity by improving soil quality, conserving water, and preventing crop loss due to pests and diseases. Improved varieties also impact the yield of staple crops positively; they boost grain yields and thereby farmers' incomes by optimizing developmental features, such as photosynthesis efficiency and increased resistance/tolerance to pests and diseases. Unfortunately, large areas of major food crops remain covered with relatively few improved varieties, and genetic uniformity is making crops vulnerable to disease and pest outbreaks and thus yield losses. Thus, the use of pesticides and herbicides is also hypothesized to influence crop productivity positively by protecting crops from pest damage.

3.3.3 Analytical Framework and Estimation Strategy

We model the adoption of the different technology combinations under the assumption that farmers take into account the net return from adoption in their decision-making process and, therefore, they choose a technology combination that provides the highest net return. Thus, we conceptualize the adoption decision behavior of farmers using the latent variable concept. Suppose that farmer *i* producing a crop at time *t* adopts a technology set *m* if the expected benefit of adoption (y_{iA}) is greater than the corresponding expected return from non-adoption (y_{iNA}), that is, y_{iA}-y_{iNA}>0 (Pitt, 1983). Letting Y_{itm}^{*} be the latent variable that captures the benefit from adopting the five technologies and their combinations (m), the relationship can be specified as:

$$Y_{itm}^{*}=\beta X_{itm}+\mu_{i} \qquad \text{where} \qquad Y_{itm}=\begin{cases} 1 & \text{if} \quad Y_{it1}^{*}>0 \\ & \quad . \\ & \quad . \\ & \quad . \\ 0 & \text{otherwise} \end{cases} \qquad m=1, 2,\ldots M \qquad (1)$$

where *Y* is an observable categorical variable that equals 1 if the farmer adopted at least one of the five specified inputs or a set of the technologies and zero if not adopted; β is a vector of parameters to be estimated; *X* is a vector of plot-, household-, and community-level variables that affect the adoption decision; μ is the error term normally and independently distributed with mean zero; and variance σ^2 measures the measurement errors and factors unobservable to the researcher but known to the farmer. Depending on the number of categories (technology combinations) Equation (1) has *m* number of regime equations including non-adoption.

As explained, the farmer chooses the technology that provides a higher expected return than not adopting, implying that the adoption decision analysis is plagued with self-selection bias (Greene, 2012; Heckman, 1979). That is, adopters and non-adopters may be systematically different from one another and this difference may be revealed in their yield performance, which may lead to an incorrect conclusion that the impact comes purely from adoption. We, therefore, employ the MESR model combined with the Mundlak approach that controls for time-varying individual heterogeneity.

3.3.4 Empirical Specification

In this paper, we estimate the MESR model combined with the Mundlak approach (Mundlak, 1978, Kassie et al. 2018) and unbalanced panel data (see Wooldridge, 2012) to estimate the impact of the different combinations of PETs and SWC on crop yield. In addition to the selection bias problem in the adoption process, the yield calculation, which is computed as the total output divided by harvested area, is based on farmer estimates that may be inaccurate. To account for such biases, we use the MESR model (Greene, 2012; Wooldridge, 2012). We choose the MESR model over the simple random and fixed effects panel data models because we detected the presence of time-varying heterogeneity in our data (Maddala, 1983; Wooldridge, 2010). The switching regression model also allows the technology choice sets to interact with the observable variables and unobserved heterogeneity (Kassie et al., 2018). Moreover, the switching regression model takes into consideration that farmers' adoption/production and consumption decisions as simultaneous.

Several studies have employed MESR models to address the problem of getting proper counterfactual, correction self-selection bias, and controlling for unobservable farm and household heterogeneity (Abdulai and Huffman, 2014; Amare et al., 2012; Becerril and Abdulai, 2010; Kassie et al., 2018; Teklewold et al., 2013). In our case, we estimate the inverse mills ratio (IMR) using the theory of truncated normal distribution and latent factor structure. However, if there is a correlation between the error terms of the outcome equations, estimating without accounting for this will lead to biased estimates. Thus, separate regressions for each of the outcome equations in which the IMR computed from the selection equation to correct for selection bias in the second stage estimation is necessary. This means that the effect of technology choice is not limited to the intercept of the outcome equations (see Zeng et al., 2015), but can also have a slope effect.[14] The adoption of five improved technologies/practices, whether PETs (chemical fertilizer, HYV, and pesticide and/or herbicide) or SWCs (terracing and contour ploughing), involves 32 technology choice sets including an "empty" set in which none of the improved inputs is adopted. Different combinations of the technologies are observed for each of the four crops. Out of the 32 choice sets, five (for barley, teff, and wheat) and seven (for maize) appear to satisfy the combined test in the adoption equation. Therefore, we estimated five yield equations for barley, seven for maize, five for teff, and five for wheat.

[14] We use a chow test to see if the different combined practices have significantly different slopes.

We estimate the pooled ordinary least squares (OLS) following Wooldridge (2002) and pooled selection models using the Mundlak (1978) approach. In doing so, we include the means of the time-varying explanatory variables as additional explanatory variables in both the adoption and outcome equations to control for unobserved heterogeneity (Mundlak, 1978). The Mundlak device combines the fixed-effects and random effects estimation approaches. By including the mean of time-varying explanatory variables, we control for time-constant unobserved heterogeneity. The estimation of MESR framework involves a two-step estimation procedure. In the first step, the multinomial logit (MNL) model accounting for unobserved individual heterogeneity is estimated to generate the inverse Mills ratio. For the MNL model, we checked whether the IIA assumption is met (Dubin and McFadden, 1984).

The five technologies with their combinations considered here comprise three PETs (chemical fertilizer, HYV, and pesticide) and two SWC measures (terracing and contour ploughing). These technologies are commonly practiced in the study area. As mentioned above, we base our analysis on the latent variable concept and assume that a household chooses a technology set that maximizes its expected net return every time. Following Kassie et al. (2015), we specify the net return of adoption as a function of exogenous variables including household and plot characteristics averaged at the household level, as well as regional and time dummies. The probability that a farm household adopts a technology set *m* at time *t* on a crop conditional on x_{it} can be represented as:

$$\text{Prob}\left(j \middle| X_{it}, Z_i = \frac{\exp(a_i + X_{it}\beta_m + Z_i)}{\sum_{k=1}^{m} \exp(a_k + X_{it}\beta_k + Z_i)}\right) \quad , \quad m = 0, 1, 2 \ldots 5/7 \qquad (2)$$

where *i* represents an individual farmer; *m* represents a technology set; *t* represents time; a_m is the specific constant term of technology set m; X_{it} represents a matrix of observable explanatory variables that affects the probability of adoption; Z_i denotes a time-constant unobserved heterogeneity term, and β_m represents unknown parameters to be estimated. As discussed above, the unobserved heterogeneity (Z_i) will be replaced by the mean of the time-varying explanatory variable (X_i), following the Mundlak approach. Equation (2) is estimated using the MNL model based on household-level unbalanced panel data. To implement the Mundlak approach, we include the means of all time-varying covariates. In the second stage of the MESR, the yield equation[15] is estimated for each of the four crops and adopters and non-adopters separately,

[15]The chow test is used for slope differences in the outcome equations.

controlling for the endogenous nature of technology adoption decisions. The yield equations for each of the crops are specified as follows:

$$\begin{cases} \text{Regime 0: } \ln Y_{it0} = V_{it0}\beta_0 + \lambda_{it0}\sigma_0 + H_{i0} + \varepsilon_{it0} & \text{if } m = 0 \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . \\ \text{Regime m: } \ln Y_{itM} = V_{itM}\beta_M + \lambda_{itM}\sigma_M + H_{iM} + \varepsilon_{itM} & \text{if } m = M, 1, 2 \ldots 5/7 \end{cases} \quad (3)$$

Where m = 0 denotes that neither of the technologies nor their combinations was adopted and m = 1,2 . . . 7 represents the adoption of either technology or their combinations; lnY_{itM} denotes the crop yield for household *i* at time *t* with technology *m*; and $\ln Y_{it0}$ represents yield for household *i* at time *t* with no adoption. V_{it} denotes observable household, plot, and community characteristics, including a time period dummy (*T*), that affects crop yield at time *t*; β and σ are parameters to be estimated, and the covariance between the error terms and adoption and outcome equations, respectively. H_i is the time invariant unobservable household heterogeneity; $\hat{\hat{\lambda}}$ is the inverse Mills from Equation (6-9) to capture time-varying individual effects (Dubin and McFadden, 1984). As in the choice model, the time invariant unobserved variable ($\bar{H}$) is parameterized by the mean values of time-varying explanatory variables $\bar{Z}$. Moreover, regional dummies are included in our estimation to capture temporal and spatial differences in agroecology, price, and institutions. The challenge in estimating counterfactuals is the fact that they are unobserved, meaning that we do not observe what would have happened had the farmer not adopted the different technology combinations leading to potential selection bias and unobserved heterogeneity (Heckman, 1979). Selection bias arises when technology adoption is voluntarily decided or some technologies are targeted to a given group of farmers. For instance, relatively wealthy farmers could be those who adopt modern technologies; in this case, self-selection into technology adoption is the source of endogeneity (Hausman, 1978).

After estimating the yield equations of each of the four crops, the average treatment effect (ATE) and the average treatment effect for the treated (ATT) are estimated (Gregory, 2015). The ATE is defined as the effect of treatment on a person selected at random from the given population relative to the effect on that person had he or she not received the treatment. This is the difference between the treated and untreated state for a given person (Gregory, 2015). To evaluate the causal effect of adoption, the expected and counterfactual outcomes are computed. The actual expected outcomes that are observed in the data are estimated as:

$$E(\ln Y_{iktM}|m=M) = V_{itM}\beta_M+\lambda_{itM}\sigma_M+\widehat{V}_{iM}\omega_M \tag{4}$$

On the other hand, the counterfactual expected value of crop yield for household i with a technology set m that contains one or more improved technologies is given as follows:

$$E(\ln Y_{ikt0}|m=M) = V_{itM}\beta_0+\lambda_{itM}\sigma_0+\widehat{V}_{iM}\omega_0 \tag{5}$$

where the parameters β_0, σ_0, and ω_0 are coefficients obtained from the estimation of crop yield without a technology set (m = 0) and other variables are as defined above. Taking the difference between Equations (5) and (6) gives the average effect of technology on adopters (Gregory, 2015), often described in the literature as the average treatment effect on the treated (ATT). The ATT can be derived as:

$$\begin{aligned} ATT_{ym} &= E(\ln Y_{it1}|m=M)- E(\ln Y_{it0}|m=M)) \\ &= (\beta_m-\beta_0)V_{itm}+(\sigma_M-\sigma_0)\lambda_{itM}+(\omega_M-\omega_0)V_{iM} \end{aligned} \tag{6}$$

The first two terms of Equation (6) indicate yield change due to the difference in returns to observed characteristics and time-invariant unobserved characteristics, and the last term indicates changes in crop yield due to time-varying unobserved heterogeneity differences. The present analysis is performed on four rounds of unbalanced household panel datasets spaced two to three years apart. The outcome variable crop yield is calculated as output per hectare of land for each of the four crops using farmer estimates.

3.3.5 Estimating the Determinants of Crop Yields

As a robustness check for the MESR model, we estimate the effect of the different combinations of the technologies along with the other control variables using the random-effects model following the Mundlak approach and (Wooldridge, 2010). The Mundlak device combines the fixed-effects and random-effects estimation approaches. The model is specified for each crop as follows:

$$\ln Y_{ikt} = V_{it}\beta + \lambda_{it}\sigma + H_i + +\varepsilon_{it} \tag{7}$$

where Y_{ikt} = represents the natural logarithm of the kth crop yield for household i at time t; V_{it} denotes observable household, plot, and village characteristics including the technology combinations and a time period dummy (T); β and σ are parameters to be estimated and the covariance between the error terms and adoption and outcome equations, respectively. H_i is the time invariant unobservable household heterogeneity parametrized by the means of the time; $\hat{\hat{\lambda}}$ is the inverse Mills ratio from Equation (2) that captures time-varying individual effects (Dubin and McFadden, 1984). As in the choice model, the time invariant unobserved variable ($\bar{H}$) is parameterized by the mean values of time-varying explanatory variables. Equation (7) shows the Mundlak random effects model.

3.4 Results and Discussion

3.4.1 Descriptive Results

Table 3.1 presents the sample means and standard deviations of the outcome variable (crop yields) and the means and standard deviations of the explanatory variables included in the regression model. The results are based on the four-round panel data of teff, maize, wheat, and barley producers collected between 2012 and 2019. The results show that on average about 85% of the sample households were headed by men and that maize and barley were the main crops grown, followed by wheat and teff, respectively. Over the four panel rounds, on average maize has the highest yield, followed by wheat and barley. Unsurprisingly, teff has the lowest yield of the four crops. However, it is a highly valued crop as it is considered a superior staple in the country. On average, about 10%, 40%, 30%, and 20% of the sample households produced teff, maize, barley, and wheat over the four rounds, respectively. Like many other countries, it is common that smallholders in Ethiopia produce different mixes of crops, especially in the main (meher) season. The pooled data of the four survey rounds shows that 187 households produce both barley and wheat in addition to other minor crops. About 52 of the sample households produce barley, wheat, and maize.

Regarding the socio-economic characteristics of the households, farmers in the study area have an average of 3.5 years of schooling and a mean family size of seven. At least three of the family members are of working age (between 15 and 64). On average, 46% of the family members are dependent, these are mostly children. The number of livestock owned and land size under all crops seem to be the same over the panel rounds. On average, households own 2 ha of total land including grazing or pasture land if they own any at all. Farmers cultivate an average of 0.9 ha of their land under the four crops considered in this study.

Concerning the use of improved technologies, over the four rounds, the descriptive results show that households tend to spend more on chemical fertilizer. On average, chemical fertilizer is also the most adopted technology with 85% of the sample households having applied it on some share of their plots. On average, it can be observed that about 33%, 32%, and 41% of the households adopted pesticides or herbicides, terraces, and contour ploughing, respectively.

Table 3.1 Sample means and standard deviations of the variables in the regression model

Variables	**2012**		**2014**		**2016**		**2019**		**Pooled**	
Independent variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Natural logarithm of kilograms of maize produced on a hectare of land	7.43	0.80	7.40	0.90	7.30	0.80	7.5	1.0	7.4	0.85
Natural logarithm of kilograms teff produced on a hectare of land	6.14	0.63	6.40	0.70	6.65	0.71	6.2	0.8	6.4	0.7
Natural logarithm of kilograms wheat produced on a hectare of land	7.33	0.66	7.14	0.73	7.14	0.73	7.4	0.7	7.2	0.7
Natural logarithm of kilograms barley produced on a hectare of land	7.14	0.64	7.00	0.81	7.10	0.70	7.12	1.0	7.1	0.8
Proportion of farmers producing teff (%)	9	0.3	15	0.35	12	0.33	11	0.32	11	0.31
Proportion of farmers producing maize (%)	40	0.49	26	0.44	25	0.43	36	0.48	37	0.48
Proportion of farmers producing barley (%)	28	0.44	33	0.47	35	0.47	29	0.45	29	0.45
Proportion of farmers producing wheat (%)	21	0.41	25	0.43	27	0.44	22	0.41	21	0.41
Distance from extension office (minutes)	3.55	0.95	3.50	0.93	3.34	0.90	3.34	0.9	3.45	0.94
Household characteristics										
Male-headed households (1=male)	0.86	0.35	0.84	0.37	0.82	0.40	0.82	0.38	0.84	0.36
Education of the household head (years)	3.42	3.30	3.34	3.64	3.11	3.50	3.43	3.1	3.42	3.2
Age of the household head (years)	45.7	14	46.4	14	49.7	14	50	14	49	14
Family size	6.5	2.3	6.5	2.3	6.7	2.6	6.4	2.33	6.6	2.3
Dependency ratio	0.48	0.2	0.48	0.2	0.46	0.2	0.47	0.2	0.47	0.2
Number of working household members	3	1.3	3	1.3	3	1.6	3.2	1.4	3	1.4
Other explanatory variables										
Poverty status (1=non-poor)	0.26	0.44	0.61	0.48	0.73	0.44			0.54	0.49
Farm size (ha)	2.04	1.64	1.80	1.28	2.04	1.97	1.96	1.33	1.95	0.65
Number of livestock (TLU)	5.36	5.08	5.41	5.06	5.32	5.14	4.8	5	5	5.02
Log of total acreage under all crops	1.01	0.48	0.92	0.41	0.99	0.45	0.34	0.27	0.82	0.4
PETs										
Log of total expenditure on chemical fertilizer	5.3	2.88 0	6.30	1.02	6.43	0.98	5.2	2.6	5.75	1.6
Log of total expenditure on pesticide and herbicide	2.2	2.3	2.4	2.5	2.03	2.6	1.7	2.4	2.4	2.1
HYV (%)	39	0.5	44	0.5	45	0.5	39	0.6	41.75	0.6
Chemical fertilizer (%)	80.5	0.4	87	0.35	90	0.31	80	0.4	85.66	3.7
Pesticide and/or herbicide (%)	34	0.3	36	0.35	28	0.29	34	0.3	33	0.3
SWC										
Terraces (%)	10	0.23	43	0.44	46	0.4	29	0.5	32	0.4
Contour ploughing (%)	25	0.48	34	0.49	39	0.5	69	0.3	41.75	0.4

Table 3.2 reports the differences in household characteristics as well as crop yields between adopters and non-adopters of the different combinations of PETs and SWC practices. The data used is pooled data from the four rounds (2012-2019). The mean yield for the four main crops is measured as the ratio of total output (tons[16]) to the area of land cultivated (ha) for each of the crops. The mean yield for teff, maize, wheat, and barley is higher for adopters than non-adopters in general. Maize producers who adopted only fertilizer have the highest yield. The few producers who applied only SWC techniques with no complementary PETs reported lower mean maize yields. The highest teff yield is among farmers who combined chemical fertilizer, HYV, terraces, and pesticide/herbicide. On average, the lowest mean teff yield is recorded among non-adopters and those who adopted only terracing or contour ploughing. Wheat producers using the combinations of chemical fertilizer, HYV, terraces or chemical fertilizer, HYV, and pesticide have the highest mean yield compared with non-adopters and adopters of other technology combinations. Overall, crop yields are higher for adopters who jointly adopted chemical fertilizer, and HYV complementing with at least one of the specified soil and water conservation practices compared with the non-adopters and those who have not adopted the corresponding combination.

Adopters and non-adopters seem to have no difference in terms of their distance from the agricultural extension office measured in minutes using the usual form of transportation. Regarding the agro-ecological zones, 14%, 30%, 55%, and 1% of the sample households reside in the Kolla, Woina Dega, Dega, and Wurch agro-ecological zones of the country, respectively. The average age of adopters is 47.5 and of non-adopters is 49. Adopters and non-adopters have no significant difference in their number of family members nor dependency ratio or economically active family labor. Adopters and non-adopters also have the same proportion of headship on average.

[16] 1 metric ton=1,000kg

Table 3.2 Differences in household characteristics for adopters and non-adopters, 2012, 2014, 2016, and 2019 pooled data

Variables	**Input combinations[17] (using pooled data from 2012, 2014, 2016, and 2019)**								
	$F_1V_0T_0C_0P_0$	$F_1V_0T_0C_1P_0$	$F_1V_1T_0C_1P_0$	$F_1V_1T_0C_0P_1$	$F_1V_0T_0C_1P_1$	$F_1V_1T_0C_1P_1$	$F_1V_0T_1C_1P_0$	$F_1V_1T_1C_1P_0$	$F_0V_0T_0C_0P_0$
	C(1)	**C(2)**	**C(3)**	**C(4)**	**C(5)**	**C(6)**	**C(7)**	**C(8)**	**C(9)**
Cereal yield (ton/ha)	1.479	1.713	1.472	1.728	1.740	1.796	1.546	1.679	1.531
Maize (ton/ha)	4.37	2.001	1.93	2.170	2.19	1.309	1.800	2.14	2.41
Teff (ton/ha)	1.12	0.74	0.916	0.562	0.760	0.554	0.866	3.35	0.584
Wheat (ton/ha)	1.476	1.385	1.019	2.226	1.690	1.565	1.558	2.183	0.460
Barley (ton/ha)	1.249	1.491	1.833	1557	1.471	1.658	1.403	1.597	1442
Male-headed	0.8	0.7	0.9	0.8	0.8	0.8	0.6	0.8	0.9
Education (years)	2.7	3.2	3.6	4.1	3.4	3.3	1.6	4.6	2.5
Age (years)	45	47	49	42	46	46	49	45	49
Family size	6	6.9	7	6.6	6	6.7	6.5	7	6
Dependency ratio	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.5
Family labor	3	3.2	3.6	3.3	3.1	3.3	3.2	3.9	3.1
Farm size (ha)	1.4	1.7	1.9	2.3	2.1	2.5	1.5	2.0	1.1
TLU	4.2	4.6	6.4	6.6	5.2	6.1	4.0	5.8	3.6
Dist. Ext. office (minutes)	46	43	35	58	43	44	77	28	36

[17] Other minor combinations of the technology are also included in the computation (see Appendix Table A1).

3.4.2 Econometric Results

3.4.2.1 Impact of Agricultural Technologies on Crop Yield

In this section, we present the results of the two-stage MESR model (Table 3.3) and the random effects model (Table 3.4). The outcome variables in both estimations are the natural log of the crop yields. Given the presence of time varying and time invariant unobserved heterogeneity, we employ a two-stage MESR model combined with the four-round panel data and the Mundlak approach. Following the Mundlak approach, we also run a random effects model and the results are qualitatively similar to those of the MESR model.

The MESR result is consistent with the descriptive results, which showed a positive association between the adoption of multiple technologies and crop yield. The actual, counterfactual, and ATT on adopters is presented in Table 3.3. The ATE is the effect of the treatment on a person selected at random from the given population relative to the effect on that person had he or she not received the treatment (Gregory, 2015). The ATE (Column D) is the estimated difference between the actual expected yield (Column A) and the counterfactual (Column B).

It can be observed that there are significant differences in crop yields when a combination of technologies is used and when none are used. Barley yield is highest for farmers who have adopted a combination of at least three of the technologies. Maize producers are the largest beneficiaries of the technologies as the difference between the actual expected and the counterfactual yield is very high. The impact of the technology sets tends to have an inconsistent effect on wheat and teff yields. This can be justified by the fact that for some of the technology combinations wheat and teff producers are very few, making estimation difficult in this particular case.

Table 3.3 Impact of the combined technologies on crop yield (log kg/ha)

		Outcomes by adoption status			
Crops	Technology combinations	Actual outcome (yield if household adopt technology set choice m)	Counterfactual outcome (yield if household did not adopt technology set choice m)	ATT	Sig.
		A	C	D = A - C	
Maize	$F_1V_0T_0C_0P_0$	8	3.4	4.6	***
	$F_1V_0T_0C_1P_0$	7.6	3.3	4.3	***
	$F_1V_1T_0C_1P_0$	7.1	3.4	3.7	***
	$F_1V_1T_0C_1P_1$	7.7	3.3	4.4	***
	$F_1V_0T_0C_1P_1$	7.4	3.2	4.2	**
Barley	$F_1V_1T_0C_0P_1$	7.1	6.0	1.1	***
	$F_1V_0T_1C_1P_0$	8	6.3	1.7	***
	$F_1V_0T_0C_1P_1$	7.03	6.1	0.9	**
	$F_1V_1T_1C_1P_0$	6.97	6.01	0.9	na
Teff	$F_1V_0T_1C_1P_0$	6.7	6.7	0	na
	$F_1V_0T_0C_1P_1$	7.6	7.4	0.2	***
	$F_1V_1T_1C_1P_1$	6.1	5.6	0.5	**
Wheat	$F_1V_0T_0C_0P_0$	7.6	7	0.6	**
	$F_1V_0T_0C_0P_1$	6.6	2.5	4.1	***
	$F_1V_1T_0C_1P_0$	7.3	7	0.3	***
	$F_1V_1T_0C_0P_1$	7.1	6.6	0.5	**

Note: *, **, *** indicate significant differences at $\alpha = 0.10$, $\alpha = 0.05$, $\alpha = 0.01$, respectively. F, V, T, C, and P refer to chemical fertilizer, HYV, terraces, contour ploughing, and pesticide, respectively; subscript "0" denotes non-adoption while "1" denotes adoption.

3.4.2.2 Determinants of Crop Yield

The results shown in Table 3.4 are estimates of a random effects model using the Mundlak approach. The problem of heteroskedasticity is detected in the data and, hence, following Greene (2012), we used robust standard errors in the analysis. The estimated results show that the agricultural inputs considered in the present paper have strong explanatory power regarding the productivity of smallholders. Attributes of the household head, such as gender, education, and age as well as the number of economically active household members appear to have no significant effect on teff and maize yields. The age of the household head is negatively and significantly associated with barley yield. The number of working household members is negatively and significantly associated with wheat and barley yield, indicating the overuse of family labor in the production of those crops.

With regard to the improved technologies considered, all the significant coefficients have the expected signs for all of the crops except on terracing or contour ploughing, which show a negative association with teff yield. This could be because of a limitation of our analysis, which is that we have only employed dummy variables that measure the extent of adoption. The number of livestock owned is not a significant factor on yield, while farm size is negatively associated with maize and barley yields.

The sample households reside in three of the five agro-ecological zones of Ethiopia. Therefore, agro-ecological zones are hypothesized to have either a negative or positive effect on crop yield. Compared with Kolla (warm, semi-arid), the Woyina Dega (cool, sub-humid) agro-ecological zone has relatively high wheat and barley yield. On the other hand, the regression results do not show a significant difference between the yield levels of the Dega (cool, humid) and Kolla (warm, semi-humid) agro-ecological zones. Distance from the agricultural extension office appears to influence wheat and barley yield positively. This can be explained by the fact that extension offices in Ethiopia nowadays are close to the Kebelles where local development agents assisting the farmers are stationed. In this particular model, there is no regional difference in the production of the four crops. The results also reveal that crop yield is significantly increasing over the three survey rounds.

Table 3.4 Random effects model estimates

Variables	Teff			Maize			Wheat			Barley		
	Coef.		SE	Coef.		SE	Coef.		SE	Coef.		SE
Gender of the household head (=1 if the household head is male)	0.02		(0.15)	0.12		(0.10)	-0.27		(0.113)	0.01		(0.13)
Education	-0.001		(0.03)	0.001		(0.02)	0.014		(0.015)	-0.002		(0.01)
Age	-0.03		(0.02)	0.01		(0.02)	-0.01		(0.02)	-0.04	**	(0.02)
Number of working family members	-0.02		(0.19)	0.02		(0.15)	-0.35	**	(0.16)	-0.24	*	
$F_1V_0T_0C_0P_0$	0.50	***	(0.20)	-0.03		(0.20)	0.786	***	(0.23)	0.28	*	(0.16)
$F_1V_0T_0C_1P_0$	0.28		(0.25)	0.13		(0.22)	0.692	***	(0.22)	0.51	***	(0.16)
$F_1V_0T_0C_0P_1$	0.47	**	(0.21)	0.36	*	(0.21)	0.916	***	(0.20)	0.43	**	(0.2)
$F_1V_1T_1C_0P_0$	-0.73		(0.94)	-0.25		(0.29)	1.098	***	(0.41)	0.69	**	(0.33)
$F_1V_1T_0C_1P_0$	0.28		(0.19)	-0.09		(0.20)	0.595	**	(0.24)	0.56	*	(0.32)
$F_1V_1T_0C_0P_1$	-0.14		(0.22)	0.33	*	(0.19)	1.118	***	(0.20)	0.55	***	(0.16)
$F_1V_0T_1C_1P_0$	0.24		(0.36)	0.36	*	(0.21)	0.716	***	(0.28)	0.43	**	(0.19)
$F_1V_0T_0C_1P_1$	0.43	**	(0.18)	0.07		(0.18)	0.810	***	(0.19)	0.46	***	(0.16)
$F_1V_1T_1C_1P_0$	0.66	*	(0.34)	0.24		(0.24)	1.040	***	(0.26)	0.55	**	(0.22)
$F_1V_0T_1C_1P_1$	-0.07		(0.45)	0.75	**	(0.31)	0.939	***	(0.25)	0.32		(0.26)
$F_1V_1P_1T_1C_1$	0.21		(0.24)	-0.07		(0.32)	0.804	**	(0.33)	0.53	**	(0.22)
$F_1V_1T_0C_1P_1$	-0.15		(0.24)	-0.33		(0.23)	0.663	***	(0.22)	0.40	*	(0.24)
Poverty status (=1 if the household is non-poor)	-0.12		(0.13)	0.04		(0.10)	0.218	**	(0.10)	0.14	*	(0.08)
Number of livestock owned (TLU)	0.01		(0.01)	0.01		(0.01)	0.013		(0.01)	0.01		(0.01)
Farm size (ha)	-0.01		(0.03)	-0.08	**	(0.04)	-0.02		(0.04)	-0.10	***	(0.02)
Distance from extension office (minutes)	0.001		(0.00)	-0.001		(0.001)	0.002	**	(0.001)	0.002	**	(0.001)
2014	0.28	**	(0.13)	-0.24	**	(0.11)	-0.407	***	(0.10)	-0.30	***	(0.08)
2016	0.58	***	(0.12)	-0.27	**	(0.11)	-0.287	***	(0.10)	-0.13		(0.10)
2019	0.3		(0.14)	0.2	***	(0.11)	0.14	**		0.1	*	(0.07)
N	**246**			**618**			**487**			**640**		
Prob > chi2	**0.005**			**0.000**			**0.000**			**0.000**		

*Robust standard errors are given in parentheses. *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively. The dependent variable is the natural log of crop yield measured as output per hectare of land[18]. The coefficients for the mean of the time-varying predictor variables and the mean of the inverse Mills ratio were not significantly different from zero. Some of the insignificant variables were not reported.

[18] Crop yield (kg/ha) for each crop was calculated as the ratio of total output produced to farmer-estimated plot size.

3.5 Conclusion and Recommendations

Ethiopia's government has placed much emphasis on agricultural development in general and improving staple crop yields in particular. Despite the efforts, however, evidence shows high crop yield gaps in the country. In the present paper, we employ a two-stage multinomial endogenous switching regression model combined with the Mundlak approach and four rounds of panel data collected between 2012 and 2019 from 390 rural households to analyze the impact of the adoption of single or sets of agricultural technologies particularly chemical fertilizer, HYV, terraces, and contour ploughing on the yield of maize, teff, wheat, and barley. Based on the observed technology combinations of the producers seven, five, five, and five separate yield equations are executed for maize, teff, barley, and wheat, respectively. It is, therefore, from these regressions that the expected counterfactual outcomes are calculated. Alternatively, the determinants of crop yield is estimated using the random effects model approach.

The descriptive results show that the attributes of the household head, such as gender, education, and age, as well as the number of economically active household members, affect wheat yield significantly. The age of the household head is negatively and significantly associated with barley yield. The number of working household members is negatively and significantly associated with wheat and barley yield, indicating the overuse of family labor in the production of those crops. The technology combinations appear to have the expected signs when they are used in combination with other complementary technologies, compared with single technology adopters. The results also indicated that single technology adopters have the lowest gains from adoption. We find that compared with non-adopters, adopters have 44%, 56%, and 69% higher yield gains in teff, barley, and wheat, respectively. The limitation of our study is the way we measure the PETS and SWC where the adoption of a single technology or several set of technologies is represented as dummy variables that denote whether the technologies are applied by the household by any of the plots with no consideration to the intensity or timing of application. Therefore, our results should be taken as indicative rather than definitive. Nonetheless, our results do confirm the positive impacts of improved technology combinations associated with crop yields. Based on our findings, we conclude that policy intervention that encourages farmers to complement different improved technologies helps them to fill the existing yield gap. Moreover, special support given to marginalized households improves the household's access to productive resources such as technologies.

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Appendix

Table A1 Random effects model estimates

VARIABLES	Teff			Maize			Wheat			Barley		
	Coef.		SE									
Gender of the household head (=1 if the household head is male)	0.02		(0.15)	0.12		(0.10)	-0.276		(0.113)	0.01		(0.13)
Education of the household head (years)	-0.001		(0.03)	0.001		(0.02)	0.014		(0.015)	-0.002		(0.01)
Age of the household head (years)	-0.03		(0.02)	0.01		(0.02)	-0.01		(0.02)	-0.04	**	(0.02)
Number of working family members	-0.02		(0.19)	0.02		(0.15)	-0.35	**	(0.16)	-0.24	*	
$F_1V_0T_0C_0P_0$	0.50	***	(0.20)	-0.03		(0.20)	0.786	***	(0.23)	0.28	*	(0.16)
$F_0V_1T_0C_0P_0$	-0.21		(0.73)	0.05		(0.22)	-0.065		(0.25)			(0.13)
$F_0V_0T_0C_1P_0$	-0.48	**	(0.22)	-0.05		(0.23)	0.299		(0.42)	0.07		(0.2)
$F_1V_0T_1C_0P_0$	-1.23	***	(0.30)	0.05		(0.42)	1.090	***	(0.30)	0.55	***	(0.21)
$F_1V_0T_0C_1P_0$	0.28		(0.25)	0.13		(0.22)	0.692	***	(0.22)	0.51	***	(0.16)
$F_1V_0T_0C_0P_1$	0.47	**	(0.21)	0.36	*	(0.21)	0.916	***	(0.20)	0.43	**	(0.2)
$F_1V_1T_1C_0P_0$	-0.73		(0.94)	-0.25		(0.29)	1.098	***	(0.41)	0.69	**	(0.33)
$F_1V_1T_0C_1P_0$	0.28		(0.19)	-0.09		(0.20)	0.595	**	(0.24)	0.56	*	(0.32)
$F_1V_1T_0C_0P_1$	-0.14		(0.22)	0.33	*	(0.19)	1.118	***	(0.20)	0.55	***	(0.16)
$F_1V_0T_1C_1P_0$	0.24		(0.36)	0.36	*	(0.21)	0.716	***	(0.28)	0.43	**	(0.19)
$F_1V_0T_0C_1P_1$	0.43	**	(0.18)	0.07		(0.18)	0.810	***	(0.19)	0.46	***	(0.16)

$F_1V_1T_1C_1P_0$	0.66	*	(0.34)	0.24		(0.24)	1.040	***	(0.26)	0.55	**	(0.22)
$F_1V_0T_1C_1P_1$	-0.07		(0.45)	0.75	**	(0.31)	0.939	***	(0.25)	0.32		(0.26)
$F_1V_1P_1T_1C_1$	0.21		(0.24)	-0.07		(0.32)	0.804	**	(0.33)	0.53	**	(0.22)
$F_1V_1T_0C_1P_1$	-0.15		(0.24)	-0.33		(0.23)	0.663	***	(0.22)	0.40	*	(0.24)
Minor combinations (dummy, =1 if a household adopted minor combinations)	0.04		(0.16)	-0.28		(0.24)	0.464	**	(0.22)	0.35		(0.22)
Non-poor (dummy, if the household is non-poor)	-0.12		(0.13)	0.04		(0.10)	0.218	**	(0.10)	0.14	*	(0.08)
Number of livestock owned (TLU)	0.01		(0.01)	0.01		(0.01)	0.013		(0.01)	0.01		(0.01)
Farm size (ha)	-0.01		(0.03)	-0.08	**	(0.04)	-0.02		(0.04)	-0.10	***	(0.02)
Agro_ecology (=1 if Woyina Dega)	-0.21		(0.24	-0.12		(0.12)	0.443	***	(0.11)	0.30	***	(0.11)
Agro-ecology (=1 if Dega)				-0.23		(0.29)	-0.244		(0.22)	-0.16		(0.19)
Distance from extension office (minutes)	0.001		(0.00)	-0.001		(0.001)	0.002	**	(0.001)	0.002	**	(0.001)
Distance from periodic market (minutes)	-0.002	*	(0.00)	-0.001		(0.001)	0.001		(0.001)	-0.00		(0.001)
Region (=1 if Oromia)	-0.24		(0.17)	-0.07		(0.11)	0.103		(0.11)	0.11		(0.09)
2014	0.28	**	(0.13)	-0.24	**	(0.11)	-0.407	***	(0.10)	-0.30	***	(0.08)
2016	0.58	***	(0.12)	-0.27	**	(0.11)	-0.287	***	(0.10)	-0.13		(0.10)
2019	0.3		(0.14)	0.2	***	(0.11)	0.14	**		0.1	*	(0.07)
N	**246**			**618**			**487**			**640**		
Prob > chi2	**0.005**			**0.000**			**0.000**			**0.000**		

Chapter Four

4. What is the Role of Improved Technologies on Farmers' Resilience to Food Insecurity in the Face of Adverse Shocks? Evidence from Ethiopia Using Panel Data

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Abstract

Ethiopia's smallholder farmers are prone to recurring and unanticipated shocks caused by weather and climate related hazards that cause substantial welfare loss. Recently, the concept of household resilience capacity determines the household's ability to absorb the negative effects of adverse shocks in poorer countries and its role to food security has been given much attention by scholars and international organizations. By using four rounds of household level panel data collected between 2012 and 2019, this paper aims to empirically measure resilience scores, and identify the determinants of household resilience as well as food security with a particular focus on technology adoption on improving household resilience as well as food security. The household resilience index is estimated by combining factor analysis and structural equation modeling. While addressing the endogeneity problem, we estimate the causal link between resilience capacity index and food security indicators with technology adoption and shocks. The results reveal that assets take the highest share in building the resilience index. Similarly, we find that adoption is significantly and positively associated with the resilience index. The higher the initial level of the resilience score the higher the current level of resilience and thus food security status. Drought shock significantly reduces the growth of the resilience score. The findings reveal that households are not able to shield themselves from the negative effects of shocks. Based on our research findings we recommend that policy interventions should exert much effort not only in promoting technology adoption but also help in building household asset holdings accompanied by improved infrastructure for smallholders.

Keywords: Ethiopia; panel data; resilience index; shock; technology adoption

4.1 Introduction

Households in developing countries particularly smallholder farmers are one of the most vulnerable social groups to shocks caused by changes in weather patterns, climatic, economic, and human-induced shocks (Dercon, 2004). As it is in most African countries, smallholder farmers in Ethiopia are disproportionately affected by weather-related shocks such as drought, flooding as well as several other human-induced shocks including conflict /political instability, animal diseases, high input prices, and imperfect product market (Carter et al., 2007). The United Nations Framework Convention on Climate Change (UNFCCC, 2014) categorized Ethiopia among the top most vulnerable countries to the adverse impacts of climate variability in sub-Saharan Africa. The effects of shocks, even small in magnitude, may have persistent negative effects in poorer countries such as Ethiopia due to the fact that particularly rural households in the country have limited capacity and resources to absorb their adverse consequences. According to (Carter et al., 2007), for instance, every Ethiopian rural household was exposed to drought at least once in the previous five years. The extent of harm, however, varies from household to household depending on the different household or community characteristics. Studies indicate that the poorest households are the most affected and often struggle to cope with shocks (Dercon, 2004; Dercon, Hoddinot et al., 2005). This group of households mostly are forced to desperate sales which is a costly and harmful coping strategy that in turn risks them entering the poverty trap.

The concept of economic resilience which is defined as "the household's ability to absorb the negative effect of adverse shocks" (Adger, 2000) has become an important research and policy issue, especially in developing countries where a significant proportion of their population are vulnerable. A household's resilience capacity is hypothesized to reduce the adverse effects of idiosyncratic and covariate shocks that the households may experience. Resilience is a multidimensional concept determined by several indicator variables known as resilience pillars. Investment on the adoption of agricultural technologies can be one of the important determinants of resilience capacity that may have a considerable role in reducing food insecurity. The use of agricultural technologies boosts agricultural productivity and yield thereby improving sales income that also ensures higher food consumption (Shiferaw et al., 2014), leading to an overall improvement of household welfare and vulnerability to adverse shocks (Kassie et al., 2011).

The measurement of resilience and its determinants has not been adequately explored partly as there are no conventional measurement approach in regard to the context of economic resilience. The measurement of resilience in the food security context is first explored by Alinovi et al. (2008, 2010). The authors estimated the resilience index by using a two stage factor analysis where in the first stage the resilience pillars are estimated using observable indicator variables and in the second stage they use the predicted values of the pillars to estimate the resilience index. The authors use cross sectional data and also shocks are not explicitly explored in their model. Using the growth model approach and panel short term panel data Vaitla et al (2012) attempted to assess the determinants of the change in welfare over time using short term panel data. Using theRIMA II approach d'Errico and Pietrelli(2017) and FAO(2018) estimated the resilience index and identified its determinants over time as well as its role in reducing the negative impact of shocks and thereby improving food security indicators. The RIMA II approach is a resilience measurement approach proposed by the FAO Resilience Measurement Technical Working Group (RMTWG) (FAO, 2018) which is evolved from the RIMA I approach applied by Alinovi et al. (2010).

This paper explores the link between changes on household welfare represented by resilience capacity index (RCI), household dietary diversity (HDD), and food consumption with the adoption of chemical fertilizer and improved seeds including their joint adoption and shocks (drought and flooding). Furthermore, we analyzed the differential effect of adoption and shocks on the outcome variables. The two technologies are chosen mainly because of their complementarity and as it is also agronomically recommended to be used as packages (Dorfman, 1996; Marra et al., 2003). The analysis allows us to measure the level of resilience capacity and its determinants as well as how livelihoods change over time which assists public intervention as well as gives insights for further research. Moreover, the study gives insights on the determinants of food insecurity and how to build household resilience. This article is organized into five sections, including the introduction. The next section provides a general concept of resilience and its measure, while section three presents the methodology and data sources. Section four presents the statistical and econometric results and a discussion of the main outputs. The conclusions and recommendations of the study are presented in section five.

4.2 The Concept and Measure of Resilience and Shocks

4.2.1 The Concept and Measure of Resilience

Recently researchers and humanitarian agencies have given much emphasis on the concept of resilience and its measure, mainly because of the increase in the frequency and severity of adverse shocks and exposure of vulnerable households (Barrett and Constas, 2014, Hallegatte, 2014). Thus, several attempts have been made to define and measure economic resilience. However, both the definitions and methodology used to measure is heterogeneous which raises the question of whether they measure one identical concept with the different methods used. In terms of the definition of resilience, according to Ellis (1998), it is defined as “the ability of a system to absorb change”. Similarly, Adger (2000) defined resilience as “the ability of groups or communities to cope with external stresses and disturbances as a result of social, political and environmental change”. But the most recent definition of resilience in the food security context is from the FAO by Alinovi et al. (2008). According to this study, resilience is the capacity of households to ensure that adverse shocks and stressors do not have long-lasting development consequences (Alinovi et al., 2010, 2008; Barrett and Constas, 2014; FAO, 2018). With regard the empirical estimation of the resilience index, the FAO Resilience Measurement Technical Working Group (RMTWG) (FAO, 2018) proposed an advanced methodology the Resilience Index Measurement and Analysis (RIMA II) evolved from the RIMA I (Alinovi et al., 2010). The RMTWG also defined resilience as “the ability of a household to keep with a certain level of well-being (i.e. being food secure) by withstanding shocks and stresses”. Other alternative approaches were also proposed by (Frankenberger et al., 2012). As our aim is to measure and identify the determinants of resilience score and its role to food security along with other determinants, particularly technology adoption.

The concept of resilience considers both ex-ante actions that reduce the risk of households becoming food insecure and ex-post actions that help households cope after a crisis occurs indicating that the analysis of resilience requires the use of panel data. Using panel data helps us capture the dynamics of household welfare and the factors determining the change over time. Resilience is not also easily observed or is considered as latent that its measure requires the use of several indicator variables called resilience pillars. These resilience pillars are unobservable themselves. Thus, resilience is created using composite indices which can be computed by combining the various dimensions in an appropriate way in order to create the resilience index (Krishnakumar, 2007). Note that the measure of resilience and vulnerability is quite different. Vulnerability is measured using a single indicator variable such as household income or consumption expenditure where its measure helps to show the susceptibility of people to damage when exposed to particular adverse shocks (Biru et al., 2020). Resilience, on the other hand, is a multidimensional concept measured by several indicator variables known as resilience building blocks or pillars. To construct the resilience score, we have used four resilience pillars (see Appendix Table A1). Agricultural technology and experience to shocks, however, are not considered in the computation of the resilience index in our case as these are the main covariates of our regression models.

Households may experience shocks that have a substantial adverse impact on their regular consumption as well as welfare. When a shock hits, households employ several coping strategies, mainly consumption smoothing, asset smoothing, and adopting new livelihood strategies such as the adoption of improved seed, in our case. On the other hand, household resilience capacity which is constituted from the different pillars also contributes to absorb and cope with shocks and helps households to bounce back to a better welfare status or to their previous state of well-being. Thus, the effects of shocks results in the long term increase or decrease in food security. This leads to the aftershock state level of food security which can also be obtained using the different resilience pillars or time variant and time invariant household characteristics. Our aim in this paper is to measure the resilience capacity of households to food insecurity and explore its effect on future household food security in the face of adverse shocks along with other important determinants of resilience and food security with a particular focus on technology adoption.

4.2.2 Estimation of Resilience

To estimate the resilience score, we employed a two-step procedure adopted from the RIMA II approach (FAO, 2018). In the first stage, the latent variable representing each pillar is estimated separately using the different observable variables by employing factor analysis (FA), and in the second stage Structural Equation Modeling-Multiple Indicators Multiple Cause (SEM-MIMIC) model is used to finally estimate the RCI using the predicted values of each of the four pillars. In the MIMIC model, the two variables representing food security household HDD and food consumption are assumed to be the achievements of resilience capacity and are observable. Thus, the food security indicators are not included in the construction of the resilience score. Figure 1 presents the path diagram of the resilience of the household model. The circles represent latent variables and the rectangles represent the observable variables.

The explanation and estimation of the four pillars[1] and their respective observable indicator variables used as well as the estimation of the RCI is presented as follows:

Access to Basic Services (ABS): access to basic services represent the ability of a household to make basic needs, and access and use of basic public services; includes, including access to infrastructure, health centers, periodic markets, agricultural extension services, and schools. Important public services including the source of drinking water; the main source of lighting; the proximity of a household (minutes taken using the usual mode of transportation) from the closest hospital, periodic market, agricultural extension center, woreda office were included under this pillar. With regard to its estimation, standard methods of factor analysis assume that the variables are continuous and follow a multivariate normal distribution. In this case, the variables are mixed (i.e. continuous and dummy), and using the simple factor analysis gives biased estimates. To solve this problem, we use a user written command (polychoric) to estimate the factor scores. With regard to the sign of the indicators variables, as expected, the source of lighting and the main toilet facility as well as source of quality water have a positive correlation with the first factor. On the other hand, the distance of the household from the periodic market and agricultural extension office is negatively correlated with the first factor. Therefore, the first factor seems to have the expected signs with the original variables and appears to be the one that explains access to basic services best. As a result, we retained the first factor in predicting the *ABS* latent variable.

Assets (AST): the assets ownership pillar comprises of both durable and non-durable assets that reflect the wealth status of the household. The observable variables used to represent assets include: the number of habitable rooms (excluding kitchen and toilet), type of roof material, agricultural land owned (ha), and livestock ownership in Tropical Livestock Unit (TLU). The entire indicator variables used to represent assets is expected to have a positive association with the latent variable measuring the asset component of resilience. This is true with the first factor where all the variables are directly related with a factor loading of greater than 0.4 following the Kasier criterion. As a result the first factor is retained and used for the estimation of the resilience index.

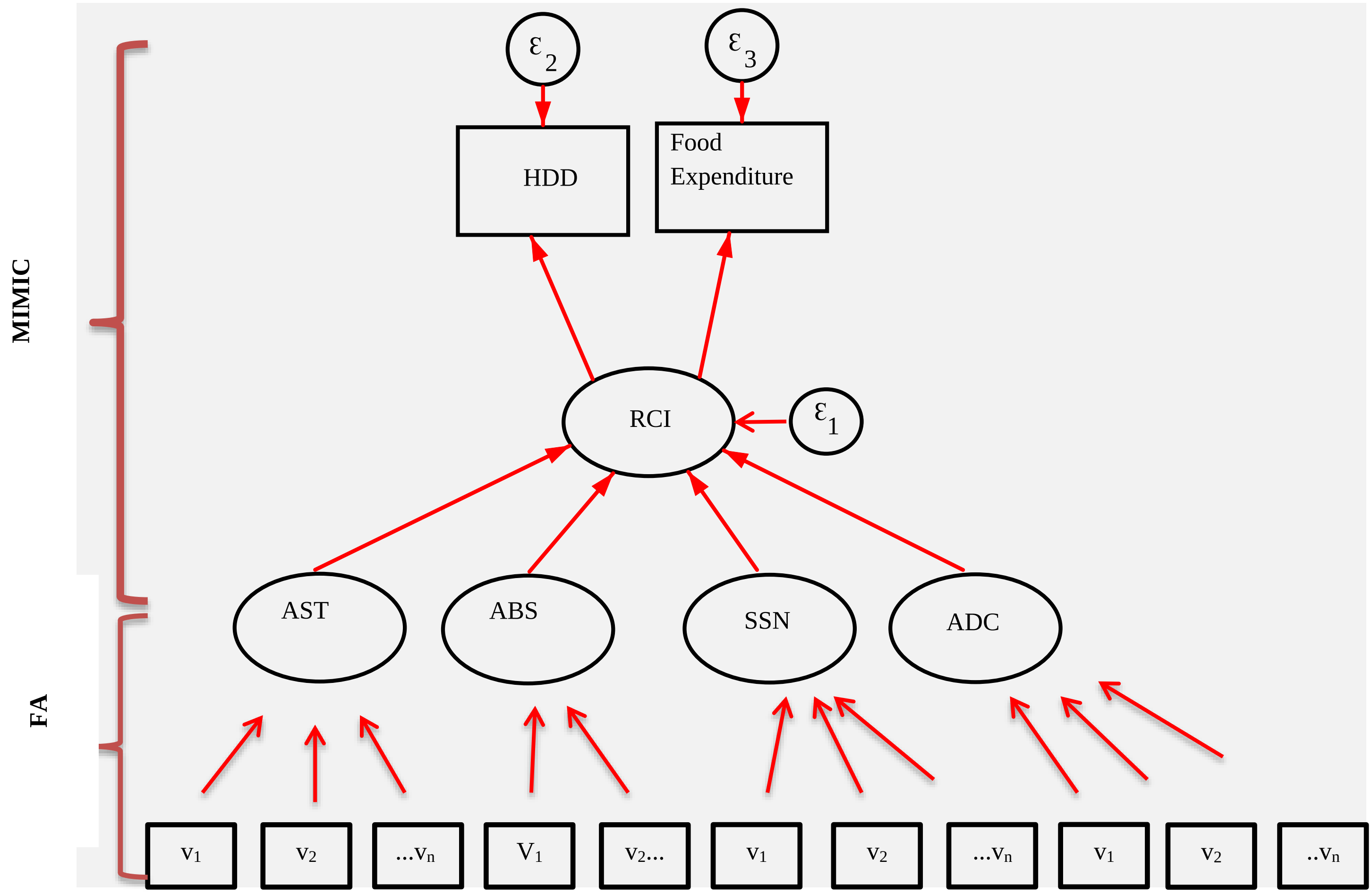
Social Safety Nets (SSN): social safety is the measure of the household's ability to get assistance from institutions as well as help from relatives and friends in case of need. *SSN* helps households

[1] All observed variables used to estimate the pillars are listed in the Appendix along with their Eigen values and factor loadings

to satisfy their basic needs and household consumption and this resilience to food insecurity (Andrews et al., 2018). Informal institutions which are comprised of strategies used for risk sharing involving social networks, norms, trust, and reciprocities such as credit networks, food, and labor sharing networks play an important role in helping households in times of shock in Ethiopia (Dejene, 2010). These arrangements help communities from adverse livelihood shocks and uncertainties. According to Dejene (2010), local informal institutions in Ethiopia are known to play important roles in assisting the poor and food insecure. In our case, social safety net is represented by membership in institutions such as credit, mahber, iqub and idirr. The first factor has the expected signs with the latent variable measuring SSN. Therefore, we retained the first factor in predicting this pillar.

Adaptive Capacity (ADC): adaptive capacity is the ability of a household to adapt to a new situation and develop new strategies of livelihood (Folke, 2006) cited by (Alinovi et al., 2010) which is linked with the existence of institutions and networks that enable the household to acquire knowledge or learn so that they are able to adjust while changes are taking place, so as to retain the same livelihood functions. According to Gallopín (2006), the capacity of adapting to perturbations and shocks is strictly connected with being able to learn from technological progress. Variables representing *ADC* component are literacy of the household head (read and write), whether the household has another source of income/remittance as well as the irrigation dummy representing whether the household uses irrigation technology. Other technology adoption-related variables that may be relevant to this pillar are not included here as our main objective is to assess the causal link between technology adoption and shocks with resilience to food insecurity. Other variables such as the demographic structure of the household affect adaptive capacity (Vincent, 2007), but as they are included as explanatory variables in our regression models, they are excluded from use in the estimation of RCI. The eigenvalues and the factor loadings of the first stage resilience estimation (FA) is reported in Table A1 of the Appendix in this chapter.

As figure 4.1 depicts the MIMIC model has two components (Bollen et al., 2010): the first component shows the links between the pillars and resilience (latent) and the second component links the RCI with thefood security indicator variables represented by HDD and food consumption which are observable.



Source: adapted from (FAO, 2018)

Figure 4.1 Path diagram of the RCI estimation of a household model

FA assumes that the residual errors are uncorrelated with each other, whereas the SEM-MIMIC approach relaxes this assumption and allows such correlation. The *RCI* is the predicted score of the four pillars (Asset, ABS, SSN and ADC). The MIMIC model assumes that all the estimated components are normally distributed with mean 0 and variance 1. The resilience scores created using the MIMIC model, however, are unitless. Therefore, to make interpretation of the regression coefficients simple, we rescale the scores into values ranging from 0 to 1. The transformation is calculated using the min-max scaling based on the simple formula: $\left(x_i^* = (x - x_{min}) / x_{max} - x_{min}\right)$.

The two components of the MIMIC model, namely the measurement component Eq. (1)- indicates the link between RCI and the food security indicators and the structural component Eq. (2), which links the estimated pillars to the RCI. Empirically, the relationship can be written as:

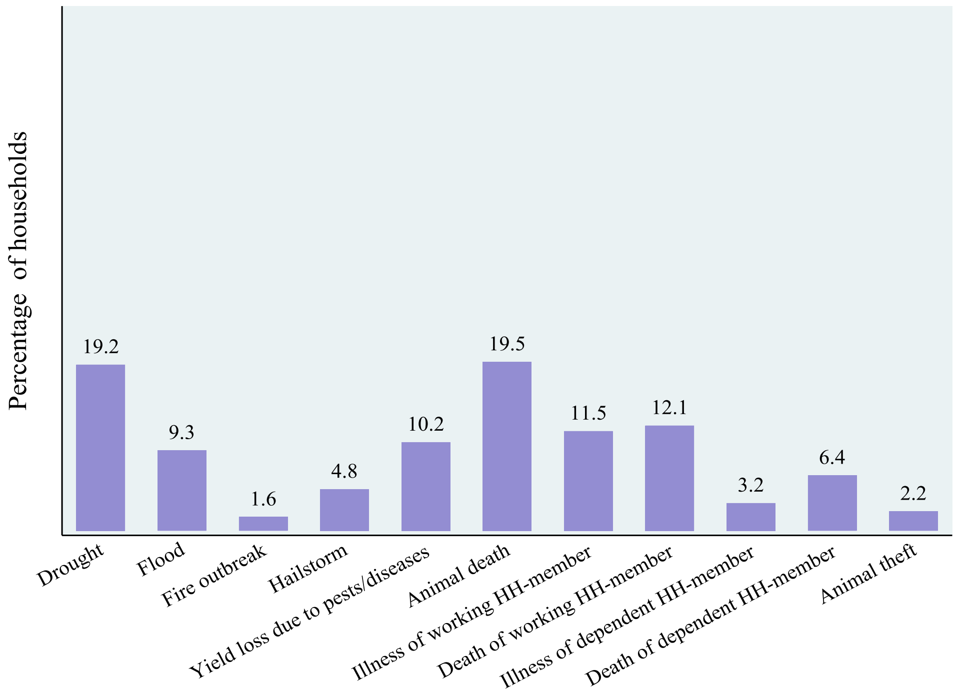
$$\begin{bmatrix} Food\ Expenditure \\ Household\ Dietary\ Diversity \end{bmatrix} = [\gamma_1, \gamma_2][RCI] + [\varepsilon_1, \varepsilon_2] \quad (1)$$

$$[RCI] = [w_{ABS}, w_{AST} w_{SSN}, w_{AC}] + \begin{bmatrix} AST \\ ABS \\ AC \\ SSN \end{bmatrix} + [\varepsilon_3] \quad (2)$$

Where *Where, RCI*=resilience capacity index; *ABS* =access to basic services; *AST*= asset; *SSN*=social safety nets; and *ADC*= adaptive capacity, w_k the weight for the k^{th} block in defining resilience; and e_i=error term. Therefore, the RCI_{it} is the predicted score of the five pillars mentioned above, considering that all the estimated components are normally distributed with mean 0 and variance 1. The MIMIC model, however,does not solve the potential endogeneity issuesarising in the model.. Therefore, this analysis is more of descriptive showing the relationship between resilience and the pillars.The causal inference is dealt in the subsequent regression analysis.

4.2.3 The Occurrence of Shocks

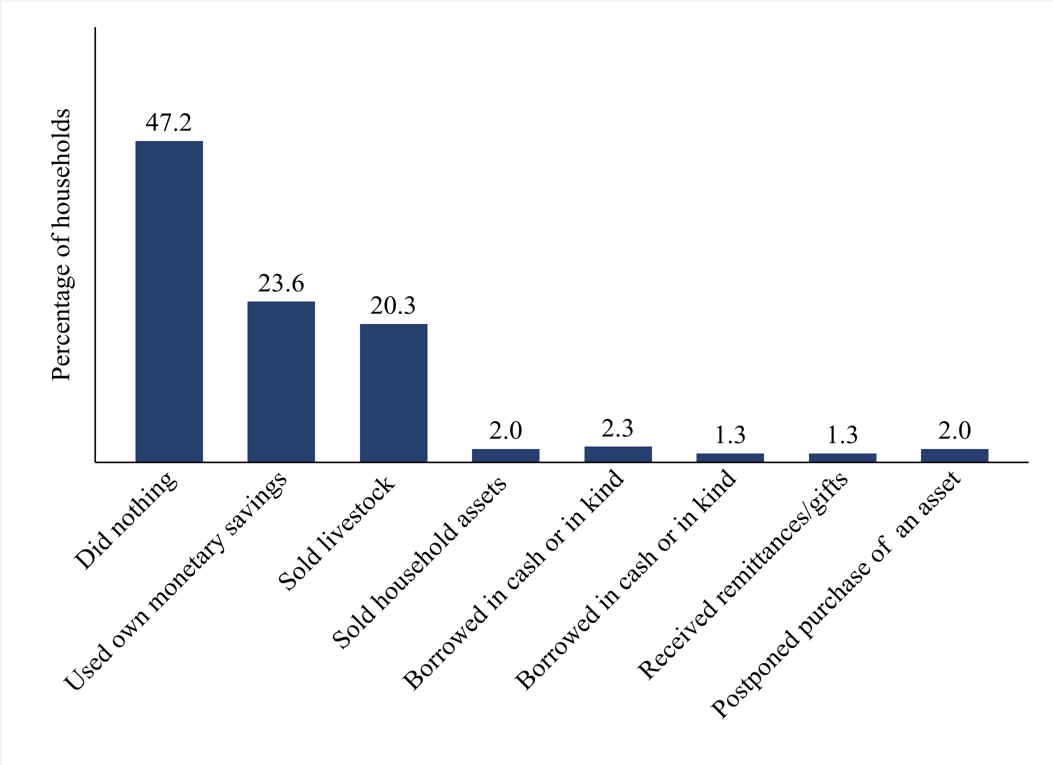
Shocks: in this sub-section, we describe the types of shocks reported in our sample households. Shocks are defined as adverse events that lead a substantial loss of household income, a reduction in consumption, and/or a loss of productive assets (Dercon et al., 2005). Household resilience capacity can be substantially reduced by shocks (Dercon, 2004; Dercon et al., 2005; Hoddinott, 2006) and this welfare deterioration and its determinants over time can be determined using panel datasets. Regarding the types of shock data, respondents were asked if shock events have happened in the past five years and if those shocks lead the household to a substantial loss or substantial reduction in their food and regular non-food consumption. In terms of shock categories, shocks are divided into a number of broad categories such as natural, market, agricultural, political, criminal shocks. The most common types of shocks reported in our sample households are drought, flooding, agricultural production and marketing related shocks. Recurrent drought has also been reported as one of the most common causes of crop failure and food shortages in the SSA, particularly Ethiopia (Shiferaw et al., 2014). Figure 4.2 presents the different types of shocks reported by the sample households using the pooled data of 2014, 2016 and 2019. Over the three panel rounds,very few households reported the same type of shock that occurred more than once in the previous five years. Regarding the proportion of households reported shocks, using the pooled data of 2014, 2016 and 2019 about 30% of the sample households reported to have experienced at least one type of shock.It can be seen that drought and animal death are the most reported shocks (19%) followed by the death of working household member (12%) and illness of working HH members (11.5%).



Source: Own computation (DFG-Ethiopia data)

Figure 4.2 Households reporting adverse shocks between 2014 and 2019

The ability of households to withstand shocks or stresses depends on the available livelihood options and on how well households are able to handle risks. Figure 4.3 reports the most important coping strategies households used to cope the reported shocks. As the figure shows, the majority (47%) of the households did nothing to cope with the shocks and about 23% and 20% of those affected by adverse shocks reported that they have used own monetary saving and sale of livestock, respectively. Other coping strategies that are reported are selling of assets, borrowing and postponing the purchase of assets.



Source: Own computation (DFG-Ethiopia data)

Figure 4.3 Households reporting coping strategies between 2014 and 2019

4.3 Methodology and Data

4.3.1 Data and study area

A household-level panel data collected in four rounds collected in 2012, 2014, 2016 and 2019 are used in this study. The household survey is collected in a random sample of 373 farm households from 29 Kebeles[2] selected in fifteen woredas (districts) of Southwestern Ethiopia, each differing in their climatic and agro-ecological characteristics (see, Biru et al., 2020). This is a follow up survey from which the sample woredas are drawn from a nationally representative baseline survey conducted in 2012 by the International Food Policy Research Institute (IFPRI) and the Agricultural Transformation Agency (ATA) of Ethiopia. Our follow-up surveys conducted in 2014, 2016 and 2019 considering the South Western parts of Ethiopia covering Oromia and SNNP regions of Ethiopia. Because of logistical and budget reasons, the sample woredas were limited to those baseline Woredas located in the specified region.

The data collection was carried out in September for the baseline survey and between March and June for the last consecutive three rounds. The household surveys were carried out using computer-assisted personal interviewing (CAPI) that ensured superior data quality through built-in consistency checks and other correction methods. The household level questionnaire collects information on demographic characteristics, asset ownership, technology and input use, consumption, production, health, risk and ambiguity. Moreover, community level data including access to infrastructure such the household's proximity to the nearest dry weather road, clean water, hospital, clinic, agricultural extension offices. The sample households were also asked to report in the previous three years if they have experienced any type of adverse shock that lead to a substantial welfare loss. Regarding tracking the sample households over the four long rounds was quite good. The attrition rate is 0% between 2012 and 2014, 2.5% between 2014 and 2016, (4%), and 2% between 2016 and 2019.

4.3.2 Conceptual Framework

Households may face both endogenous and exogenous shocks. However, we assumed the shocks considered here as exogenous that are theoretically beyond the control of the farmer. Further, we assumed that the shocks themselves are not inter-correlated. The effect of shocks on welfare can, therefore, be estimated using single equation models with the assumption that welfare indicators and exposure to shocks are linearly associated. However, estimating the

[2] The smallest administrative unit of Ethiopia

causal link between adoption and the welfare indicator variables using single equation models could lead to biased estimates because of the potential presence of endogeneity problems caused by unobserved heterogeneities (Tittonell et al., 2007).

Farmers' adoption and non-adoption decision is related to the expected net returns of adoption or non-adoption. A household adopts a technology set that maximizes the expected profit, where its returns are also dependent on several factors such as factor markets and the production function of the specific technology (Feder et al., 1985). In developing countries, household production and consumption decisions are non-separable that needs to be considered in our impact analysis. Smallholders in Ethiopia operate under a thin or missing factor and product market as well as households production and consumption decisions are non-separable. With this regard, to investigate the welfare impact of adoption, we apply a non-separable recursive household model. For simple conceptualization, suppose that *A* represents adoption (chemical fertilizer and improved seed including joint adoption), the adoption equation can be written as:

$$A=f(X,L,Z,V) \tag{3}$$

Where *X* represents variables determining the household's ability to adopt the technology choice sets, *L* is household demographic characteristics including labour endowment, *Z* is agro-ecological characteristics and *V* represents community characteristics.

The next step is linking technology adoption with the welfare indicators. Technology adoption improves resilience capacity and thus food security. Here we formulate the household welfare equation in a utility framework such that

$$W=f(A, S, L,V) \tag{4}$$

Where *W* represents household welfare (i.e. RCI, HDD andfood consumption), *S* represents shocks (drought and flooding) and other variables are as previously defined. We hypothesized that the adoption of the two inputs accompanied with other complementary soil and water conservation practices increases the level of food security for adopters and potentially reduces the negative impacts of shocks.

4.3.3 Empirical Approach

Estimation of Multiple Technology Adoption

To assess the effects of adoption and shocks on household resilience to food insecurity and the role adoption may play in averting the adverse effects of these shocks, we first estimate the adoption equation of two commonly practiced complementary inputs: chemical fertilizer and improved seed. Starting from Eq. (3) in our conceptual framework we specify the following:

$$A_{it} = \alpha + \beta_1 x_{it} + \beta_3 HH_{it} + \beta_4 V_{it} + \beta_5 T_t + \mathcal{E}_{it} \tag{5}$$

x_{it} represents variables determining technology adoption, HH_{it} household characteristics, V_{it} represents spatial or agro-ecological characteristics, T_t denotes year dummy. $\mathcal{E}_{it}$ is a compound error term consisting of unobserved time-invariant factors, c_i, and unobserved-time variant shocks, v_{it}, that affect technology adoption. In estimating Eq. (5) we used MNL model and include all exogenous variables, year and community dummies, as well as the means of time-varying variables to control for unobserved heterogeneity. This correlated random effects model relaxes the strong assumption of no correlation in a standard random-effects model (Wooldridge, 2010).

Estimating the Impact of Adoption and Shocks on the Resilience Index

The impact analysis of technology adoption on the RCI and food security indicators and its role in reducing the adverse impact of idiosyncratic and covariate shocks is the main objective this study. As outlined in the conceptual framework, we can formulate the following simplified relationship:

$$W_{it} = \eta A_{it} + \delta S_{it} + \beta' HH_{it} + \beta_4 V_{it} + \beta_5 T_t + \theta(A_{it} * S_{it}) + \alpha_i^* + \varepsilon_{it} \tag{6}$$

Where W_{it} welfare indicator (RCI, HDD and food consumption), A_{it} technology adoption sets, S_{it} shock, X_{it} is the community and household level socio-economic characteristics, α_i^* household fixed effects and ε_{it} the idiosyncratic error term. θ captures the differential effect of technology adoption and shocks. This model suffers from three potential sources of endogeneity. The first potential source of endogeneity comes from unobserved heterogeneity. Time-invariant household characteristics which are unobserved may be correlated both with adoption and with our welfare measure. The second potential source of endogeneity is selection bias, where some households, depending on wealth status, risk preference, and ability/skill are tend to adopt new technology while also having a higher welfare level. Third, the current resilience score and food security indicator variables may heavily depend on past resilience capacity causing omitted variable bias. As a result, the inclusion of a lagged dependent variable and also lagged values of some of the independent variables, in our model, is theoretically required (Wooldridge, 2012). Empirically, Eq.(6) can be re-written as follows:

$$W_{it} = \rho W_{i,t-1} + \eta A_{it} + \delta S_{it} + \beta' HH_{it} + \beta_4 V_{it} + \beta_5 T_t + \theta(A_{it} * S_{it}) + \alpha_i^* + \varepsilon_{it} \qquad (7)$$

$W_{i,t-1}$ is the lagged dependent variable (first-order lag), other variables are as defined in Eq.(6). This type of model can be estimated by first differencing within the transformation, as in one-way fixed effects models, or by taking first. This type of econometric relationships is estimated using dynamic panel data (DPD) models. Although the use of lagged dependent variables in DPD models allow for partial adjustment of the model, it causes a bias arising from the demeaning process that subtracts an individual's mean values of the dependent and each of the independent variables including the lagged dependent variable from each of the respective variable creating a correlation between regressor and error according to Nickell (1981). To resolve this issue, one prominent econometric model has been proposed by (Hsiao and Anderson, 1981) and extended by (Arellano and Bond, 1991). This model is commonly known as growth model (Dercon et al., 2009) and can be estimated using the first difference Generalized Method of Moments (GMM) model estimation. The difference GMM model uses the difference between the outcome variables at period *t* and *t-1* as the dependent variable for the period. The GMM estimates of the (Arellano and Bond, 1991) model can be written as:

$$\Delta W_{it} = \rho \Delta y W_{i,t-1} + \Delta A_{it} + \Delta S_{it} + \beta' \Delta X_{it} + \theta \Delta(A_{it} * S_{it}) + \Delta \varepsilon_{it} \qquad (8)$$

Where Δ is the change in the variables from the baseline over time, and the rest is as previously defined.. In the GMM estimation all the independent variables that are assumed to be endogenous and the lagged values of the outcome variable are instrumented using lagged values of the same variable. Compared to RE and FE models, AB estimation weaken the exogeneity assumption for a subset of regressors, thereby providing consistent estimates even if reverse causality is present.

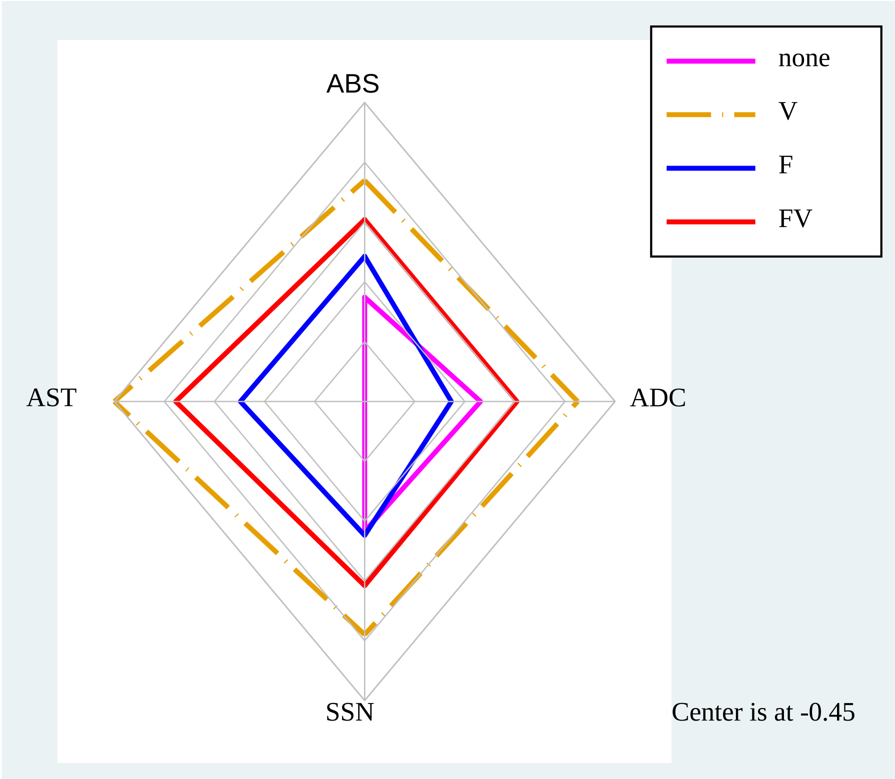
In summary, in estimating the impact of shocks and technology choice sets including their interaction, first we estimate the adoption equation using MNL model as previously outlined. Secondly, we execute the predicted probabilities from the MNL model. Finally, we estimate the welfare equation using the GMM growth model as well as IV model by instrumenting with their lagged values of the RCI and the predicted values of adoption from the MNL model. Similarly, the two other outcome variables representing food security: food consumption and HDD are estimated using the same procedure. In this case, we hypothesized that the lagged values of the RCI influence the current food security status of a household.

4.4 Results and Discussion

In this section, we present descriptive results of the outcome variables (RCI, HDD, food consumption) and the covariates both the endogenous (adoption dummies) and the exogenous variables included in the regression model. We estimated the RCI by combining FA and SEM-MIMIC model. In the MIMIC model HDD and food consumption are considered to be influenced by the resilience capacity and are directly observable and indirectly associated with the remaining four pillars (FAO, 2018).

4.4.1 Descriptive Statistics

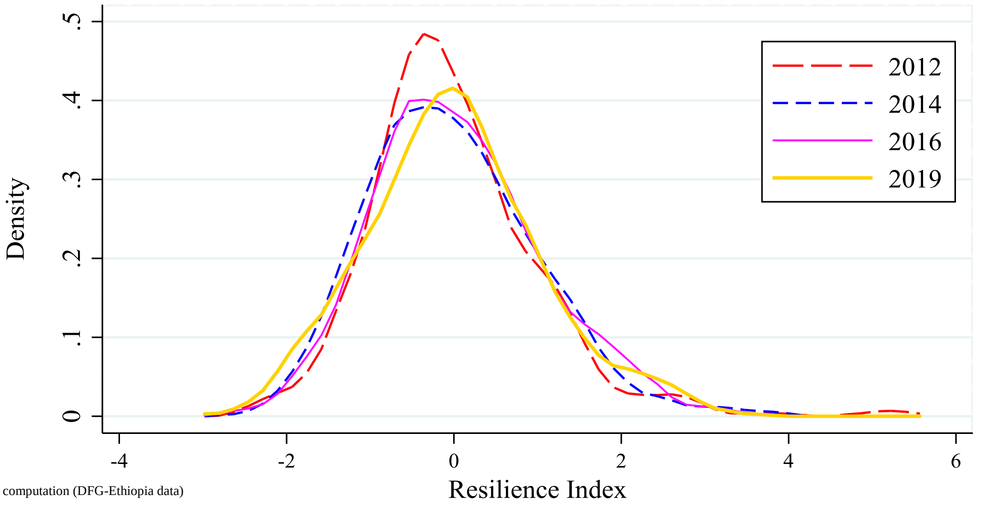
Figure 4.4 shows the radar graph for the resilience index and its pillars by the adoption status of households (i.e. single or joint adoption of chemical fertilizer and improved seed) including non-adopters where none of the technologies or their combinations is adopted. The analysis of the resilience score and its components for the different periods also reveals that the importance of the drivers is dynamic throughout the survey rounds. It is shown that households that adopted only improved seed appear to have the highest RCI even higher than those who adopted both technologies jointly. It is shown that non-adopters scored less in all of the pillars and RCI except SSN and ADC where non-adopters have a higher score compared with the fertilizer-only adopters.



Source: Own computation (DFG-Ethiopia data)

Figure 4.4 Radar graph of the resilience pillars by adoption status of households

Figure 4.5 shows the Kernel density plot used to visualize the distribution of the resilience index over the four survey rounds. The figure shows a slight difference in the resilience distribution between the first three rounds and the last round (2019). However, there is no clear difference in the means of the resilience index between the first three rounds.



Source: Own computation (DFG-Ethiopia data)

Figure 4.5 Kernel density distribution of resilience index by survey (2012-2019)

The SEM-MIMIC results presented in Table 4.1 shows that all the five pillars are statistically significant determinants of the RCI. This table also shows that the two most important drivers of resilience capacity are asset ownership (ASS) and adaptive capacity (ADC). The estimated value of RCI is unitless. Therefore, a scale is defined by constraining the food consumption variable loading (γ_1) to be 1, meaning that one standard deviation increase in RCI causes an increase in one standard deviation in food consumption.

Table 4.1 Estimation of RCI using MIMIC: coefficients of structural and measurement components

	Coeff.	sig	
Structural			
Assets (AST)	0.19	***	(0.02)
Access to Basic Services (ABS)	0.12	***	(0.03)
Social Safety Nets (SSN)	0.05	***	(0.014)
Adaptive Capacity (ADC)	0.06	***	(0.015)
Measurement			
Per capita food consumption expenditure (log)	1		
Household dietary diversity (HDD)	2.60	***	(.04)
$\chi 2$	**11.94**		
P-value	**0.007**		
Obesrvations	**1164**		

Table 4.2 presents the differences in the household characteristics by the resilience index and its pillars. The t-statistics for the pair-wise comparison among the means of the independent variables including shock categories and input combinations are also presented in this table. The pairwise comparison and the t-statistics with the technology choice sets is always compared with the non-adopters.

In terms of differences by adoption status, adopters who used at least one of the technologies have a statistically significantly higher resilience score compared to non-adopters. The same applies to the pillars where non-adopters have lower mean scores all the four pillars compared with adopters. Regarding food consumption and dietary diversity, adopters appear to have a higher mean per capita food consumption and HDD.

With regard to experience to shocks, households have no statistically significant differences in the resilience score and its pillars except in SNN score where households who did not report any shock have a higher SSN compared with those who have experienced at least one type of shocks during the study period. Specifically, there is no statistical difference in the resilience index and its pillars between households who reported drought and those who did not report. Concerning household headship, male-headed households have a higher and statistically significant resilience index compared with female-headed households. Male-headed households have higher and statistically significant scores in all of the resilience pillars but ABS compared with female-headed households. Regarding changes on the resilience score over time, we compared the mean levels of the resilience index and its score with that of the baseline (2012). The pairwise comparison shows a slight increase in the resilience index between 2012 (-0.03) to 2014 (-0.02) and in 2016 (0.04) and then dropped in 2019 (0.001). The pairwise comparison of the difference in RCI between the baseline 2012 and the last wave 2019 is not statistically significantly different from zero.

Overall, adopters of the different technology combinations including single technology adoption show a higher resilience score. However, the resilience scores more or less remains constant over time.

Table 4.2 Differences in household characteristics by the RCI and its building blocks

	Mean values of the RCI and its building blocks				
Variables	**RCI**	**ABS**	**AST**	**ADC**	**SSN**
F_0V_0	-0.45	-0.08	-0.46	-0.04	-0.06
F_0V_1	0.44***	0.36***	0.47***	0 .13	0.48***
F_1V_0	-0.06***	-0.04	-0.03***	-0.16*	-0.01
F_1V_1	0.26***	0.05**	0.23***	0.20***	0.12***
HHs reported shock	0.03	0.01	0.01	-0.09	-0.12
HHs reported no shock	-0.05	-0.003	0.002	0.03	0.07***
HHs reported drought	-0.01	0.11	-0.002	0.20	0.01
HHs with no drought experience	0.01	-0.01	0.03	0.01	0.01
Female headed households	-0.38	.055***	-0.26	-0.75	-0.15
Male headed households	0.07***	-0.01*	0.05***	0.14***	0.03***
2012	-0.03	-0.01	-0.03	-0.01	-0.01
2014	-0.02	-0.07	-0.14	0.08	-0.23
2016	0.04	0.02	0.01	0.01	0.32
2019	0.001	0.06	0.13	-0.10	-0.06
N					1116

Note: *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively. F and V represent chemical fertilizer and improved seed respectively; subscript "0" denotes non-adoption while "1" denotes adoption.

Table 4.3 presents the changes in household food security indicators over the last three panel waves. Considering only the three waves, we computed proportion of households that experience a loss in the two food security indicator variables. About 38% of the sample households experienced a decline in HDD between 2014 and 2016 and a little less (35%) experienced a decline in HDD between 2016 and 2019. Out of those households who experienced a decline in HDD, 43% of them were able to recover in 2019. In terms of food consumption, the proportion of households experiencing a decline in food consumption between 2014 and 2016 is quite high (60%) compared to the proportion of households experienced decline food consumption between 2016 and 2019 (36%). Only 20% of the households were able to recover from the loss of food consumption on 2019.

Table 4.3 Changes in food security status between two periods

Changes in food security status		
HDD	N	%
Households experienced a decline between (2014 -2016)	149	38
Households experienced a decline between (2016-2019)	140	35
Households recovering from loss (2014 and 2019)	106	43
Per capita food consumption		
Households experienced a decline between (2014 -2016)	236	60
Households experienced a decline between (2016-2019)	143	36
Households recovering from loss (2014 and 2019)	106	28

The means and standard deviations for resilience and its building blocks by survey year is given in Table 4.4 As explained, the main objective of this paper is to Analyse the impact of adoption and adverse shocks as well as their differential effects on the welfare outcome variables. Using the two inputs (chemical fertilizer and improved seed), four possible combinations including non-adoption where none of these technologies are adopted can be constructed. Thus, adoption is represented by four dummy variables (F_0V_0, F_0V_1, F_1V_0, F_1V_1). Shocks and Household demographics such as gender, age, household size, and dependency ratio that are not used to construct the resilience pillars are included in our regression models.

The descriptive results show that the resilience index increased in the first three rounds and then somehow dropped in the last round. On the contrary, the joint adoption of chemical fertilizer and improved seed shows an increasing trend over time (26%, 33%, 39%, and 40% in 2012, 2014, 2016, and 2019, respectively). On average, the proportion of non-adopters remains constant between 2012 and 2014 (24%) but then decreased to 16% in 2016 and again increased to 21 % in 2019. Concerning the demographic characteristics of households, the average size of the household is more or less the same (on average 6) throughout the survey rounds. The dependency ratio which is 47% and the gender of the household head did not also change over the survey rounds. The proportion of non-adopters of the two technologies or their combinations is the same between 2012 and 2014 and constantly decreased between 2014 and 2019. The proportion of households adopting only improved seed only decreased from 9% to 4% and 3% for the first three respective rounds and again slightly increased to 4% in the last round. On the other hand, the proportion of fertilizer only adopters which is the highest technology choice set in our sample is the same throughout the survey rounds (40%). The proportion of households adopting chemical fertilizer and improved seed variety jointly (F_1V_1) consistently increased over the four survey rounds.

The different types of shocks including drought, flooding, animal death, death of a family member, high input price and low sales price are included in the regression model. In terms of the frequency of reported shocks, more households reported adverse shocks in 2019 followed by the 2014 round. The proportion of households that reported at least one type of shock for the previous three years decreased between 2014 and 2016 (29% versus 23%) but then increased to 36% in the 2019. Out of the households who reported shocks in 2014, 2016, and 2019, on average, 2%, 11%, and 2% were affected by droughts, respectively. Moreover, a significant proportion of households 29% in 2014, 22% in 2016, and 36% in 2019 have reported flooding shocks. Households took about six months to recover to their normal welfare level. Regarding the reduction of food or regular consumption, about 19%, 13%, and 22% reduced their food consumption in 2014, 2016, and 2019 due to shocks, respectively. Likewise, 18%, 14%, and 19% of households were forced to reduce their regular consumption in 2014, 2016, and 2019, respectively.

Table 4.4 The descriptive statistics of the variables in the regression model

		2012		2014		2016		2019		Pooled	
Variable	**Description**	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
RCI	Resilience Capacity Index (Standardized , 0 to 1)	0.33	0.11	0.34	0.12	0.35	0.12	0.34	0.13	0.34	0.12
HDD	Household Dietary Diversity	6.88	1.4	6.51	1.7	6.50	1.7	6.67		6.64	1.6
Household size	Number of family members	6.25	2	6.4	2.2	6.5	2.3	6.4	2.3	6.4	2.3
Gender	Dummy, 1= if the household head is male	0.84		0.83		0.83		0.83		83.4	
Dependency ratio	The ratio of working to non-working hh members	0.48	0.2	0.47	0.2	0.46	0.2	0.47	0.2	0.47	0.2
Age	Age of the household head in years	45	14	46	14	49	13.7	50	14.3	47.5	14
F_0V_0	None adopters of chemical fertilizer and improved seed	0.24		0.24		0.20		0.16		0.21	
F_0V_1	Proportion of households adopted high yielding variety	0.09		0.04		0.03		0.04		0.05	
F_1V_0	Proportion of households Fertilizer and improved seed	0.40		0.38		0.38		0.39		0.39	
F_1V_1	Proportion of households adopted chemical fertilizer	0.26		0.33		0.39		0.40		0.34	
Shock exp.	HHs reported shocks past three years			0.29		0.23		0.36		0.29	
Drought	Drought experience the past three years			0.02		0.11		0.02		0.05	
Flooding	Proportion of households experienced shock			0.29		0.22		0.36		0.29	
Hailstorm	Proportion of households reporting hailstorm			0.03		0		0.02		0.01	
Yield Loss	Proportion households reported yield loss			0.05		0.002	8	0.03		0.03	
Animal death	Proportion of households reporting animal death			0.04		0.013		0.11		0.05	
Recovery months	Number of months the hh took to recover to normal			4.6	6	3	5	8	10	6	7.5
Regular Cons.	Proportion of households reduced regular consumption			0.18		0.14		0.19		0.17	
Food consumption	Proportion of households reduced food consumption			0.19		0.13		0.22		0.18	
N					**372**					**1116**	

Note: *, **, *** indicate significant differences at α = 0.10, α = 0.05, α = 0.01, respectively.

F and V refer to chemical fertilizer and improved seed, respectively; subscript “0” denotes non-adoption while “1” denotes adoption

4.4.2 Impact Assessment on Resilience and Food Security

The assessment of the impact of technology adoption and shocks on welfare is undertaken by representing welfare by RCI, HDD, and per capita food consumption. We employed the GMM model following (Arellano and Bond, 1991) to estimate the impact of adoption and shocks on resilience growth. Furthermore, we executed the instrumental variables (IV) regression model instrumenting the technology dummies with their lagged values and the predicted probabilities of adoption from the first stage MNL adoption equation. As a robustness check for the IV model estimates, we also executed mixed Tobit model regression, but, by using only data from the last three rounds; due to the lack of shock information in the baseline survey.

Table 4.5 presents the GMM estimator (column 1), IV (column 2), and the mixed Tobit (column 3) model estimates. In terms of the model results, the signs of both the endogenous and exogenous variables have the expected signs and are qualitatively similar to that of the IV and mixed Tobit results. However, very few variables seem to be significant in the difference GMM consistent with the descriptive results which show a negligible change in resilience capacity over the survey rounds. The results indicate drought has a statistically significant negative impact on the growth of the resilience capacity index. Family size increases the growth of the resilience score statistically significantly. It is also shown that resilience in 2016 was significantly higher compared to the other survey rounds. Our findings (Column 2 of Table 4.5) show that the initial value of the resilience capacity, the technology choice sets (F_0V_1 and F_1V_1), gender of the household head, household size, and age of the household head are statistically significant determinants of the resilience index. Specifically, male-headed households have a statistically significant and higher level of resilience index compared to female-headed households. Household size statistically significantly increases the RCI. A unit increase in the initial value of the RCI increases the current RCI[21] by 0.5 points. Age has a statistically significant negative impact on the resilience index. The adoption of F_0V_1 significantly leads to a higher resilience score.

Overall, Our findings show initial resilience index, technology dummies (F_0V_1 and F_1V_1), gender of the head, household size, and age of the household head determine the resilience index significantly. Drought appears to significantly decrease the growth resilience score.

[21] In this paper the terms resilience index and resilience capcity or RCI are used interchangeably.

Table 4.5 Impact of adoption and shocks on resilience capacity index

Variables	**Description**	**(1) GMM**			**(2) IV**			**(3) Tobit**		
RCI_{t-1}	Initial resilience capacity	0.05		(0.07)	0.51	***	(0.05)	0.561	***	(0.02)
HH size	Number of household members	0.006	***	(0.003)	0.005	**		0.003	***	(0.002)
Gender	Sex of the household head	0.02		(0.02)	0.02	**	(0.01)	0.02	***	(0.01)
F_0V_1	Dummy=1, if HH adopted only improved seed	0.007		(0.04)	0.50	*	(0.30)	0.10	***	(0.02)
F_1V_0	Dummy=1, if HH adopted only fertilizer	0.003		(0.01)	0.04		(0.04)	0.02	**	(0.01)
F_1V_1	Dummy=1, if adopted both improved seed and chem. Fertilizer	0.002		(0.02)	0.06	**	(0.03)	0.05	***	(0.01)
Drought	Dummy=1, HH reported drought shock	-0.04	*	(0.02)	0.02		(0.05)	-0.01		(0.03)
Flood	Dummy=1, HH reported flood shock	-0.02		(0.02)	-0.01		(0.02)	-0.0004		(0.02)
Age	Age of the HH head (years)	-0.0003		(0.001)	-0.001	***	(0.00)	-0.001	***	(0.001)
Drought* F_0V_1	Interaction term drought and improved seed	-0.01		(0.06)	-0.42			-0.02		(0.05)
Drought* F_1V_0	Interaction term drought and chemical fertilizer	-0.001		(0.02)	-0.03		(0.06)	-0.01		(0.04)
Drought* F_1V_1	Interaction term drought and improved seed and fertilizer	-0.02		(0.03)	-0.01		(0.05)	-0.01		(0.04)
SNNPRs	Dummy=1, if SNNPRs region									
2016	Dummy=1, if 2016 survey round	0.01	*	(0.01)	0.015		0.01	0.020	**	
2019	Dummy=1, if 2019 survey round	0.004		(0.01)	-0.01		0.009	-.001		
R^2 or Log-likelihood					0.26					
Sample size		**1,119**			**1,119**			**746**		

Note: *, **, *** indicate significant differences at $\alpha = 0.10$, $\alpha = 0.05$, $\alpha = 0.01$, respectively.
F and V refer to chemical fertilizer, improved seed, respectively; subscript "0" denotes non-adoption while "1" denotes adoption. In the GMM model, F_0V_1, F_1V_0 and F_1V_1 were instrumented with their lagged values and all the lagged explanatory variables included in the model.

Table 4.6 reports the IV regression model executed by instrumenting the resilience index and technology dummies with their lagged values. The OLS and mixed Tobit estimates for robustness check are also presented in Columns 2 and 4. The outcome variables in these models are represented by real per capita food consumption expenditure and HDD.

As Table 4.6 column 1 indicates, demographic characteristics of the household such as family size and gender of the household head are statistically significant determinants of consumption. The higher the household size the higher the household per capita food consumption. Regarding, technology adoption, chemical fertilizer only or improved seed only, or their joint adoption are positively and significantly linked to food consumption. In terms of shocks, drought statistically and significantly decreases food consumption. This significant and negative sign confirms our hypothesis that shocks reduce household assets and production, thus reducing household food insecurity. Although, not statistically significant the interaction terms between the technology dummy and drought ($Drought*F_1V_1$) is positive indicating the role of adoption of multiple technologies in slightly smoothing the negative impact of shocks.

Column 2 of Table 4.6 presents the estimates of the IV regression model on the impact of adoption and shocks HDD as the outcome variable. The results indicate that household characteristics such as gender of the household head and household size affect dietary diversity positively and significantly. The adoption of chemical fertilizer and improved seed including their joint adoption also significantly increases household dietary diversity. The interaction terms of the technology bundles and drought representing shock are not statistically significantly different from zero in this model.

Overall, the results reveal that the adoption of chemical fertilizer and improved seed including their joint adoption increases food consumption and HDD. Although the adoption of chemical fertilizer and improved seed including their joint adoption increases the resilience capacity index as well as the food security indicators, there is limited evidence regarding its impact in averting the adverse impacts of shocks.

Table 4.6 Impact of adoption and shocks on food consumption and HDD

		Food Consumption						HDD					
		(1) IV			**(2) Tobit**			**(3) IV**			**(4) Tobit**		
RCI_{t-1}											3.3	***	(0.42)
Age	Age of the HH head (years)	0.0003		(0.001)	0.0001		(0.0004)	-0.01		(0.01)	-0.01		(0.01)
Gender	Sex of the household head	0.002		(0.02)	0.01		(0.01)	0.58	**	(0.23)	0.58	***	(0.22)
Household size	Number of household members	0.01	***	(0.003)	0.01	***	(0.002)	0.10	***	(0.04)	0.11	***	(0.04)
F_0V_1	Dummy=1, HH adopted only improved seed	0.47	*	(0.25)	0.13	***	(0.03)	0.90		(0.57)	0.90	*	(0.55)
F_1V_0	Dummy=1, if HH adopted only fertilizer	0.28	**	(0.12)	0.07	***	(0.02)	0.67	*	(0.36)	0.67	*	(0.35)
F_1V_1	Dummy=1, adopted improved seed and. Fert	0.23	***	(0.08)	0.06	***	(0.02)	1.04	***	(0.35)	1.04	***	(0.33)
Hailstorm	Dummy=1, HH reported Hailstorm shock	-0.06		(0.04)				-2.66	*	(1.61)	-2.66	*	(1.55)
Yield loss	Dummy=1, HH reported yield loss shock	-0.05	*	(0.03)	-0.04		(0.05)	-0.31		(0.96)	-0.32		(0.92)
Animal death	Dummy=1, HH reported animal death shock	-0.03		(0.02)				-0.19		(0.73)	-0.18		(0.70)
Drought	Dummy=1, HH reported drought shock	-0.04	**	(0.02)	-0.03		(0.03)	-0.11		(0.57)	-0.11		(0.55)
Drought * F_0V_1	Interaction term drought and F_0V_1	-0.05		(0.06)	-0.05		(0.06)	0.59		(1.04)	0.59		(0.99)
Drought*F_1V_0	Interaction term drought and F_1V_0	-0.001		(0.04)	-0.01		(0.04)	-0.46		(0.70)	-0.45		(0.67)
Drought*F_1V_1	Interaction term drought and F_1V_1	0.02		(0.04)	0.02		(0.04)	-0.08		(0.69)	-0.08		(0.67)
R^2 or log-likelihood		**0.14**			**965**			**0.03**			**2140**		
Sample size		**1119**											

Note: *, **, *** indicate significant differences at $\alpha = 0.10$, $\alpha = 0.05$, $\alpha = 0.01$, respectively.
F and V refer to chemical fertilizer and improved seed; subscript “0” denotes non-adoption while “1” denotes adoption.

4.5 Conclusion and Recommendation

Smallholder farmers in developing countries particularly in Ethiopia are disproportionately affected by natural shocks such as drought, flooding as well as several other human-induced shocks including conflict, political instability, and inflation. This often results in significant welfare deterioration since smallholders in these regions have a minimal absorptive capacity. Investment in the adoption of agricultural technologies plays important role in building the resilience capacity and potentially reducing food insecurity. This study uses panel data collected between 2012 and 2019 to identify the determinants of household resilience to food insecurity and assess the role of chemical fertilizer and improved seed including their joint adoption on the resilience capacity and food security of smallholders and the role these inputs may play in reducing the adverse effects of shocks.

The four resilience pillars used to construct resilience capacity appear to be significant determinants of the resilience capacity index and assets take the highest share. It is also evident that adopters have a significantly higher resilience index compared with non-adopters. On the other hand, The findings also reveal that adopters and non-adopters have no significant differences in terms of their proneness to shocks. The findings reveal that joint or single use of chemical fertilizer and improved seed are significant determinates of resilience capacity index, household dietary diversity, and food consumption. Drought is negatively and statistically significantly linked with the growth of the resilience capacity index. Other variables determining household dietary diversity and consumption expenditure are gender and age of head and household size. The results also show the current level of the resilience score is highly and positively influenced by the the previous years' resilience capacityIt can also be seen that adoption has a limited role in protecting households from the adverse impacts of shocks. Based on our research findings we recommend that policy interventions should exert much effort not only in promoting technology adoption but also in building resilience more importantly asset asset building accompanied by improved infrastructure for smallholders.

4.6 Reference

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Appendix

Table A1 The eigenvalues and the factor loadings of the pillars used to estimate the RCI

Pillars	Variable	Factor loadings	
		Factor1	Pillars' correlation with the var.
ABS	Source of light	0.50	0.30
	Type of toilet	0.42	0.27
	Distance from market	-0.66	-0.42
	Distance from agricultural extension office	-0.67	-0.42
	Source of drinking water	0.50	0.31
AST	Livestock (TLU)	0.60	0.3
	Land (ha)	0.49	0.27
	Number of rooms	0.80	0.42
	Corrugated iron roof	0.76	0.42
SSN	Iqub	0.69	0.56
	Iddir	0.52	0.43
	Mehaber	0.37	0.31
	Credit	0.56	0.46
ADC	Education	0.75	0.65
	Other income	0.72	0.62
	Irrigation	0.25	0.22

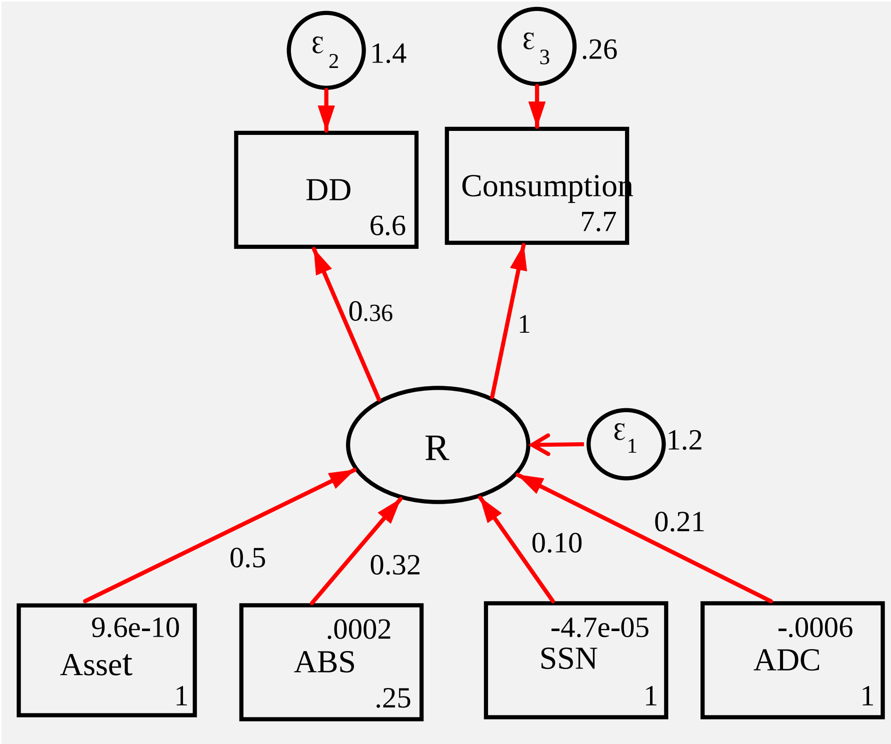

Figure A1 Resilience path diagram

Chapter Five

5. General Discussion and Policy Implications

Despite fast economic growth in the last three decades, a significant proportion of Ethiopia's population faces pervasive poverty, food insecurity, and vulnerability to poverty. The problem is more pronounced in rural households whose livelihood entirely depends on subsistence rain-fed agriculture. In response, there have been significant efforts made by the incumbent government and non-government organizations in disseminating agricultural technologies, improved practices along with farmer training through extension agents to boost agricultural productivity and production in the country. Despite the efforts, agricultural technology adoption rates, however, are quite low and the intended benefits of adoption may have not been realized by smallholders. Moreover, farmers are prone to the frequent occurrence of adverse shocks that are responsible for the perpetuation of poverty and food insecurity in Ethiopia. The effects of shocks can be severe simply because smallholders' coping or shock absorption capacity is limited. It is against this background that this thesis explores the linkages between the adoption of the different combinations of productivity-enhancing technologies and soil and water conservation practices and smallholder food and essential non-food consumption, poverty and vulnerability, crop yield, and resilience to food insecurity. These main topics were addressed by three research questions analyzed in the previous chapters. This chapter briefly presents the general discussions and summary of the findings of the thesis, contributions, and drawbacks of the methodologies employed, as well as implications for smallholders' welfare improvement policies. The chapter also gives insights on the potential for future research directions.

5.1 General Discussion and Policy Implications

The main focus of this thesis is to explore the link between agricultural technology adoption, adverse shocks, and rural smallholder's welfare. Unlike the pre-dominantly univariate approach applied in many impact studies, this thesis argues that technology adoption decision is multivariate, and employing univariate modeling ignores the useful information regarding the inter-related and simultaneous adoption decisions of multiple technologies. By combining rich panel data with the use of a two stage endogenous switching regression model combined with the Mundlak approach, and related supplementary micro-econometric techniques this study analyzes the role of combinations of agricultural technologies adoption including single technology in improving consumption, reducing poverty and vulnerability as well as improving crop yield. There are considerable bodies of literature on many developing countries showing the crucial role of agricultural technology adoption to fight against poverty and food insecurity mainly focusing on a single input. This thesis addresses this gap considering multiple technology combinations of three productivity-enhancing technologies and two soil and water conservation practices on consumption, poverty and vulnerability to poverty and crop yield of smallholders presented in the second and third chapters of this thesis. The third chapter deals with a more multidimensional aspect of smallholders' welfare and its link with adoption and shocks. In this article, we specifically examined the impacts of the two widely applied technologies (chemical fertilizer and improved seed) on the resilience index and food security indicators of farm households in Ethiopia.

The second chapter explores the impact of the adoption of combinations of productivity-enhancing technologies and soil and water conservation practices including single technology adoption on smallholder's consumption expenditure, poverty, and vulnerability in Ethiopia. The results clearly show that technology adoption leads to improvements in consumption expenditure over time. The study also revealed that maximum consumption gain is achieved when multiple technologies were adopted highlighting the need for multivariate econometric analysis of adoption decisions. The econometric estimations reveal that the highest impact of adoption is observed when at least three of the five technologies considered in this study are adopted together. Recent empirical evidence by Kassie et al. (2015, 2018), Manda et al. (2016), and Teklewold et al. (2013) in Ethiopia and elsewhere also demonstrate that a combination of technologies provides higher net returns than when only a single technology is adopted. In terms of combining productivity-enhancing and soil and water conservation practices, the findings reveal that the highest impact of adoption on consumption and thus poverty and vulnerability is observed for the technology combination of chemical fertilizer and improved seed complemented with at least one of the SWC practices, which increases consumption by more than 60%. Regarding the role of adoption on poverty and vulnerability, the ordered logit model results show that the adoption of a single technology or its combinations reduces the likelihood of households being in the chronically poor, vulnerable groups and enables them to move to a better welfare situation (non-poor). In addition, the findings show that consumption, poverty, and vulnerability are influenced by several other household, socioeconomic, agro-ecological, and community characteristics. For example, we found that households with more family members are more likely to escape the chronically poor category. Moreover, we find that number of livestock is associated with a higher likelihood of being in a non-poor category signifying that asset ownership in rural Ethiopia, such as livestock, is an integral part of smallholders' welfare. In terms of location, households located in SNNPR region are less likely to escape poverty than those in Oromia.

In terms of the use of combinations of technologies, the results show that poor households tend to adopt single technologies or only soil and water conservation practices more frequently than the non-poor. As expected, the results also indicate that higher proportions of poor households are non-adopters. The non-poor tend to adopt multiple technologies than the chronically poor or vulnerable. Regarding the correlation between inputs, the marginal and conditional probability estimates of improved productivity-enhancing technologies and soil and water conservation measures, the results indicate strong complementarity among technologies; where adoption of one technology improves the likelihood of adoption of the other technology. The adoption of improved seed variety, for instance, increases the adoption of chemical fertilizer and vice versa. This is in line with several studies investigating input substitutability or complementarity (Napasintuwong and Emerson, 2004). For example, in our case, the probability of adopting chemical fertilizer when conditional on whether the household also adopted improved seed on average is greater than 85%.

Regarding the household's poverty and vulnerability status, our results revealed that a significant proportion of households are chronically poor or vulnerable. It is also clear that the household's poverty status is not stable over time. For instance, of the 290 poor households in 2012, only 46% and 28% remained poor in 2014 and 2016, respectively. Although the headcount ratio decreased over time a significant proportion of households are vulnerable suggesting that the incidence of vulnerability to poverty is more prevalent than the poverty itself, which was reported by other researchers like Haughton and Khandker (2009). In terms of gender differences, female-headed households tend to be poorer than male-headed households throughout the survey rounds, though the proportion of poor households in both gender groups declined significantly. In terms of differences in other socio-economic characteristics, compared to non-poor poor households own less livestock, have fewer economically active household members, a smaller family size with a female, and less-educated household head. Compared with non-poor households, they also experience more adverse shocks and a lower rate of technology adoption.

The third chapter examines the impact of the adoption of the combinations of the five technologies including single technology adoption on the yields of the four dominant crops in

Ethiopia (teff, maize, wheat, and barley). To achieve this objective, while controlling for unobserved heterogeneity we estimated the average treatment effect which is the effect of the treatment on a person selected at random from the given population relative to the effect on that person had he or she not received the treatment (Gregory, 2015). It is computed as the estimated difference between the actual expected yield and the counterfactual. The model results show a strong link between the adoption of multiple technologies and crop yield. Moreover, the study found that there is a significant difference in crop yields when a combination of technologies is used and when none are used or single input use. The relevance of the technology combinations varies from crop to crop. For instance, barley yield is highest for farmers who have adopted a combination of at least three of the technologies while other crops showing mixed levels of statistical significance.

Among the four crops, maize producers are the largest beneficiaries of the technologies and also the highest maize yield is achieved for only fertilizer adopters. This can be justified by the fact that for some of the technology combinations wheat and teff producers are very few, making estimation difficult in this particular case. The other important factor for the discrepancy could be the identification problem where in most cases maize varieties available in the market identified as a local variety by farmers may not be local in reality given the widespread presence of improved maize varieties in the country. Furthermore, the few producers who applied only soil and water conservation techniques with no complementary productivity-enhancing technologies have lower mean maize yields. The highest teff yield is among farmers who applied chemical fertilizer, improved seed, terraces, and pesticide/herbicide combined. On average, the lowest mean teff yield is recorded among non-adopters and those who adopted only terracing or contour ploughing. Wheat producers who applied the combinations of chemical fertilizer, improved variety, and terraces or chemical fertilizer, improved variety, and pesticide have the highest mean yield compared with non-adopters and adopters of other technology combinations.

Using the pooled data, the descriptive results show that maize and barley were the main crops grown, followed by wheat and teff, respectively. On average maize has the highest yield, followed by wheat and barley. In terms of how crop production diversity, about 10%, 40%, 30%, and 20% of the sample households are producers of only teff, maize, barley, and wheat mixed with other minor crops over the four rounds, respectively. The remaining producers produce several combinations of crops. Out of the total sample households, 187 households produce both barley and wheat in addition to other minor crops during the four rounds and about 52 of the sample households produce barley, wheat, and maize. On average, households own smaller than 2 ha of total land including grazing or pasture land if they own any at all. Farmers cultivate an average of 0.9 ha of their land under the four crops considered in this study. Crop yield is also highly influenced by agro-climatic zones. As expected, non-adopters are poorer than adopters where on average, 60% of non-adopters and 30% of adopters live below the national poverty line.

Other influencing factors of crop yield are household attributes such as gender, education, and age of head, as well as the number of economically active household members, which appear to have significant effects but are not always true to some of the crops. Gender, education, and age of head as well as family labor appear to influence barley and wheat yields but not on teff and maize yields. The age of the household head is negatively and significantly associated with barley yield. The number of working household members is negatively and significantly associated with wheat and barley yield, indicating the overuse of family labor in the production of those crops. The number of livestock owned is not a significant factor on yield, while farm size is negatively associated with maize and barley yields. The sample households reside in three of the five agro-ecological zones of Ethiopia. Therefore, agro-ecological zones are hypothesized to have either a negative or positive effect on crop yield. Compared with Dega, the Woyina Dega (cool, sub-humid) agro-ecological zone has a relatively high wheat and barley yield. Distance from the agricultural extension office appears to influence wheat and barley yield positively. This can be explained by the fact that extension offices in Ethiopia nowadays are close to the Kebelles where local development agents assisting the farmers are stationed. In this particular model, there is no regional difference in the production of the four crops. The results also reveal that cop yield is significantly increasing over the three survey rounds.

The fourth chapter is about the quantification of the smallholder’s resilience index and seeks to explore the impact of the adoption of chemical fertilizer and improved seed including their joint adoption on the different household food security indicators (resilience index, dietary diversity, and food consumption and access index). Technology adoption ensures better yield and this improves food security, dietary preference, income, and reduces vulnerability to shocks. In this chapter, we focused on two widely promoted technologies out of the several inputs that are used by the sample households mainly because of their complementarity and often recommended to be used as packages (Dorfman, 1996). In estimating the impact of shocks and technology choice sets, the lagged dependent variable and reverse causality issues are addressed by employing the

GMM model following Arellano and Bond (1991) and IV estimation with a robustness check using mixed Tobit regression.

In terms of the quantification of the resilience index, it is constructed using five resilience pillars (adaptive capacity). The results reveal that all the five pillars are significant determinants of the resilience index and a higher proportion of the resilience score is composed of asset, adaptive capacity, and social safety net pillars. The study also reveals that the importance of the pillars varies over time signifying the importance of the use of panel data. In terms of the differences in predicted values of the pillars by adoption, non-adopters scored less in all of the five pillars and thus resilience score compared to adopters except for adaptive capacity where the score is higher compared to chemical fertilizer only adopters. On the other hand, non-adopters have a better social safety net and adaptive capacity score compared with the fertilizer-only adopters. The results clearly show that adopters have higher resilience scores compared to non-adopters. On the contrary, the results show that the resilience index and pillar scores do not show any difference between those affected by a drought shock and those who have not. Even though, no differences in terms of the distribution of the resilience index between 2012 and 2016, there is slight growth in the last round (2019). Male-headed households' higher resilience index compared with female-headed households. On average, adopters have better scores in all the resilience pillars. Our findings show that the first lag of the resilience index seems to be another important factor.

The econometric results reveal that adoption is a significant driver of resilience index, dietary diversity, and food consumption. Moreover, drought shock impacts adversely affect the resilience index and dietary diversity. However, there is no evidence suggesting that the adoption of the two technologies helps farmers avert the adverse impacts of the shocks suggesting the requirements of external intervention through introducing other complementary coping mechanisms such as credit and insurance coverage. Similarly, single or joint adoption of chemical fertilizer and improved seed is crucial in improving the food consumption score. Although, not statistically significant the interaction terms between the technology dummies and drought shock is positive indicating the role of adoption in reducing the negative impact of shocks. In addition, the results reveal that adoption of the two technologies, single or jointly increases the level of household dietary diversity. Shocks such as hailstorms and drought appear to impact food consumption adversely. Other determinants of the resilience index dietary diversity are gender and age of head, family size, and dependency ratio. On average, being in a male-headed household and having a larger family size is directly associated with a higher resilience score and better dietary diversity. The results reveal that the older the household head the lesser diverse the household diet is. Dependency ratio and age of head are also significant determinates of food consumption score.

5.2 Limitations and Recommendations for Future Research

In chapter two, we measured poverty using real food and non-food household consumption expenditure and the national poverty line. In terms of measuring food consumption expenditure, we use the seven-day recall method which is considered a strong approach in providing details of short-term estimates of food intake (Hernández-Cordero et al., 2015). However, it has also weaknesses as this approach may not be suitable in capturing distant meals, irregularly consumed foods or if respondents have memory issues as well as seasonal variations of food consumption. Using nationally representative household-level data recorded monthly for a year, Hirvonen et al (2016) found that household diets in Ethiopia are highly subjected to significant seasonal changes in food supply and energy intake. In terms of exploring the link between technology adoption and household welfare outcomes, the measure of the technology variables is represented by binary variables. Although this is a widely used conventional way of measuring adoption, the use of dummy variables may not always capture the extent of adoption (Doss, 2006; Feder et al., 1985; Temple et al., 2016). Moreover, the agronomic practices such as the timing of technology application, type of soils, and how it is applied is not the focus of the study investigated in the thesis which may be interesting for further study.

In chapter three, we analyzed the impact of adoption and shocks on the resilience index as well as the food security proxy variables. In this case, the shock variables are represented by binary variables which may not also give us the extent of the damage of the adverse shocks. Overall, in terms of the impact of technologies on welfare, specifically, the use of productivity-enhancing technologies such as chemical fertilizers and pesticides has many undesirable environmental consequences which cannot be overlooked (Rockström et al., 2016) which is beyond the scope of this thesis. The inclusion of the environmental impacts of adoption is, therefore, another interesting topic for future work. Measurement issues, however, are addressed in the regression models implicitly.

5.3 Concluding Remarks/Policy Implications

Public intervention in terms of investment in providing improved agricultural practices is crucial in reducing poverty and food insecurity, but it has to be inclusive and provide opportunities for improving the livelihoods of the poor. Achieving food security and poverty reduction requires new and existing applications of science, technology, and innovation across the food system, addressing all dimensions of food security. This thesis has three main contributions. Firstly, methodologically, the study uses long-term data to analyze the impact of adoption on rural farm households' welfare. The use of panel data especially in developing countries such as Ethiopia is quite novel given the scarcity of long-term panel data from smallholders located in marginalized and mostly remote areas. Secondly, our impact analysis is based on multiple technologies, unlike, previous studies that focused on single technology adoption. To the best of the authors' knowledge, this is the only study that attempts to explore the impacts of the combinations of productivity-enhancing and soil and water conservation practices in the Ethiopian context. The approach employed in this thesis further captures the non-separability of production and consumption decisions by parametrizing the adoption decision choice sets. The use of rich long-term panel data also enables us to capture the dynamics of poverty (i.e. vulnerability to poverty).

In examining how the adoption of multiple technologies affects wellbeing, the thesis employed advanced econometric methods that circumvent the potential endogeneity problem of technology adoption. Furthermore, by combining the resilience pillars to quantify the resilience index, the study identified the impacts of adoption and shocks on the resilience capacity index and different food security indicators at the household level. In doing so, the study provides insights on the status of the household resilience capacity to food insecurity and how it is built. This provides potential entry points on how specific policy interventions, especially those related to the promotion of technology adoption to boost productivity or increase soil fertility including the adoption of improved seed varieties, input subsidy, informal credit, and off-farm employment may affect the level and distribution of income, consumption, and food security. Our results on the determinants of poverty and vulnerability as well as resilience have many relevant policy implications. Even without the absolute magnitude of the effects, policy-makers can use the results of this thesis to identify the chronically poor, vulnerable, or non-resilient groups who appear to be mostly non-adopters.

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5.4 Reference

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