Impacts of Improved Agricultural Technologies Adoption on Multidimensional Welfare Indicators in Rural Ethiopia

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Approval Sheet

This is to certify that the dissertation prepared by **TSEGAYE MULUGETA**, entitled: **"Impacts of Improved Agricultural Technologies Adoption on Multidimensional Welfare Indicators in Rural Ethiopia"** and submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Economics complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Chapter One: Introduction and Summary of the Thesis

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Abstract

This thesis consists of an introduction, one Co-authored paper and three independent single-author papers. This thesis discusses the importance of improved agricultural technologies and improved practices on multidimensional welfare in Rural Ethiopia. The introduction gives a brief summary of the four papers which form the thesis. In the first stage, a meta-analysis was done to identify the gaps in literature and learn more about the linkages between improved agricultural technologies and welfare. The papers are held together by concepts and theories associated with farm households' adoption of modern agricultural technologies, linkages between the indicators of multidimensional welfare and technology through an impact analysis in a program evaluation setting and unobservable behavior of the factors in the adoption-welfare context.

Chapter 2 (Paper 1) does a meta-analysis of improved agricultural technologies and their impact on welfare in Africa. The meta-analysis considers the results of a study of a sample of 52 empirical estimates that investigated the impact of improved agricultural technologies in Africa with a focus on three key outcomes: output or expenditure, food security, and poverty. The results show that differences in the reported impact of technologies can be attributed to several factors such as data type, model specification, theories, sample size, study area, and journal type. The study also used a test for publication bias and observed no publication bias in general.

The next two chapters (Papers 2 and 3) focus on linking multidimensional poverty, food security and child nutrition with improved agricultural technologies. Paper 2 examines the impact of adopting improved agricultural technologies on multidimensional poverty through two powerful impact evaluation techniques--propensity score matching and endogenous switching regression methods--for measuring the causal inference and the Alkire and Foster counting approach for measuring the multidimensional poverty index. The results of the empirical analysis show that adoption of technology reduced overall and living standards' deprivation scores while there were regional variations in the impact of the technology; a high reduction in deprivation was observed in Amhara region followed by the Oromiya region. Across deprivation groups the impact was higher in the severely deprived households.

Paper 3 discusses the impact of improved agricultural technologies on food security and child nutrition using a panel data through a two-ways fixed effect combined with the propensity score matching and endogenous treatment effect techniques. This paper links adoption-nutrition which has been partly neglected by most existing studies. It uses four different outcomes: consumption expenditure, child nutrition, food shortages, and household worries about food availability. The results of the first two outcome variables show that adoption had a significant positive impact while the impact of the remaining two outcomes shows that improved agricultural technologies did not affect welfare.

The last paper links improved agricultural technologies to women's empowerment in the context of impact evaluation relying on a panel data analysis and employing differences-in-differences and propensity score matching techniques in a program evaluation setting. This is a new setting in the agriculture sector. It applies the Abbreviated Women's Empowerment in Agriculture Index and its two components--five domains of the Empowerment and Gender Parity Index for measuring empowerment. The findings show that technology improved women's empowerment through five domains of empowerment, but not through the gender parity index, which implies that empowerment is derived more from its five domains.

Keywords: Technology adoption; meta-analysis; multidimensional poverty; food security; women's empowerment; Ethiopia; Africa.

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1.Introduction

Over the past few decades, several studies have presented a general picture of the agriculture sector in the sub-Saharan African (SSA) region. A continuous reduction in the productivity of food crops in developing regions including SSA is associated with numerous factors including poor adoption of improved technologies and modern practices alongside poor pest management, use of poor storage methods, and crop loss during harvesting which leads to food insecurity and poverty in these regions. The adoption of improved agricultural technologies for increasing the productivity of smallholder agriculture in developing regions that fosters economic growth and improves the well-being of millions of poor households is considered an appropriate strategy (Norton et al., 2006), as it accelerates diversification and intensification of agriculture that match growing population pressures and demand for food. New and improved agricultural technologies and practices can improve social welfare in general and in this era of globalization and development, technological innovations are one of the major factors shaping agricultural development. Several empirical studies state that adoption of new agricultural technologies and improved practices has a big role in increasing agricultural production and improving national food security in developing countries. If the application of these new technologies is successful, it could stimulate overall economic growth through inter-sectoral linkages while conserving natural resources (Faltermeier and Abdulai, 2006; Sanchez et al., 2009).

Adopting improved agricultural technologies and practices that increase agricultural productivity and promote environmental sustainability are important strategies for achieving the goals of food security and poverty alleviation in developing regions like SSA. In most of these regions, the agriculture sector is a key fundamental for raising economic growth, overcoming poverty, enhancing food security, and price control in an excess demand situation. However, low use of modern technologies and low productivity in these regions are a major developmental challenge (Asfaw et al., 2012; Deathier and Effenberger, 2012). Improving the productivity, profitability, and sustainability of smallholder farming through modern agricultural technologies is therefore the main pathway out of poverty (The World Bank, 2008). In addition, a high productivity agriculture sector helps allocate resources to service and industry sectors while maintaining a better-balanced economy.

It is also argued that experience and evidence from countries within and around the SSA region show that returns to agricultural technology development could be very high and far reaching such that they transform not only the smallholder sector, but also the entire national economies of countries in the region (Mazonde, 1993). Several studies also show that smallholder farmers have several possible ways of enhancing their welfare and their food security if they make use of improved agricultural technologies (Feleke and Zegeye, 2006; Langyintuo et al., 2008) and reduce their poverty levels (Asfaw et al., 2012; Mendola, 2007; Wu et al., 2010). This can also improve their nutritional status (Kumar and Quisumbing, 2011) and reduce the risk of crop failures (Hagos et al., 2012).

However, recent evidence shows that undernourishment has increased alarmingly and about 815 million people worldwide were undernourished in 2016 with the largest number being in Africa (FAO, 2017; Luan et al., 2013). Nearly half the population in SSA lives in poverty and the rate of poverty level in the region is twice that of the global average and the highest in the world (African Development Bank ([AfDB], 2012). About 75 percent of Africa’s poor live in rural areas where the primary economic activity is agriculture, but the agriculture sector has not been able to ensure food security in most of the SSA countries. Recent evidence also shows that about 0.8 billion people in the world were undernourished and close to 28 percent lived in SSA of which more than half were living in East Africa (FAO, 2015).

Gender-wise, evidence shows that women produce over 50 percent of the world's food (FAO, 2011a) and comprise about 43 percent of the agricultural labor force, both globally and in developing countries (Doss, 2014), though women and girls are over-represented among those who are food insecure. Evidence also shows that worldwide about 60 percent of the undernourished people are women or girls (United Nations Economic and Social Council [ECOSOC] 2007; World Food Program [WFP] 2009a). The process of empowering women in the agriculture sector to produce more food is a right way of reducing vulnerability to poverty and food insecurity as it can help increase income generated from the agriculture sector and increase food consumption (Baiphethi and Jacobs, 2009). Evidence also shows that empowering women in the agriculture sector can provide sustainable ways in which they can feed themselves leading to improvements in income from the surplus produced, which again makes them less vulnerable to both poverty and food insecurity. One major challenge in relation to gender is access to improved technologies. Relatively speaking men have better access to modern agricultural technologies. Closing this technology gap between women and men requires necessary technologies which satisfy the priority needs of women farmers, given that women are aware of their usefulness and have the means to acquire these technologies (FAO, 2011a).

1.1 Social Welfare and its Measurement

Most traditional measures of welfare indicators such as poverty, standard of living, and quality of life are based on a household unit's aggregate value of monetary income or on its consumption levels (Alkire and Sarwar, 2009). The need to understand social welfare beyond the income dimension has resulted in a significant increase in research areas on non-income and beyond income welfare status at the individual and household levels. However, the focus of most existing studies is on independent analyses of household and/or individual attributes.

The choice of income as the only dimension of measuring well-being seems inappropriate as it ignores heterogeneity across individuals in several other dimensions of living conditions. Each dimension represents an aspect of life which people value and care about including dimensions like health, literacy, and housing. A person's achievements in a dimension indicate the extent of his/her performance in that dimension, for instance, how healthy he/she is, how friendly he/she is, how much his/her monthly income is, and so on.

Bataan (2008) argues that measuring welfare, especially poverty needs to go beyond these money-metric measures in such a way that other additional components or dimensions are included in the measurement processes. The primary reason for this is that "the quality (regularity and comparability) of income/expenditures data is often poor in many developing countries" especially for those SSA countries which show the most poverty and extreme poverty. The second reason is that well-being is multidimensional by nature.

There has been a growing interest in the question of how to move beyond purely income-based measures of welfare towards measuring welfare in a multidimensional context. The concept of seeing well-being as a multidimensional phenomenon is not new and goes back to the works of, for example, Rawls (1971); Townsend (1979); Streeten (1981); Atkinson and Bourguignon (1982); Sen (1985, 1992); Stewart (1985); Ravallion (1996); Bourguignon and Chakravarty (2003); Weymark (2006); and Thorbecke (2008) . In Sen's (1985) prominent conceptual framework for the 'capability approach,' an individual's well-being is given by her capabilities, reflecting a combination of valuable and inter-related functioning (or 'beings and doings') that she can attain in various domains of life.

Sen expanded on the notion of human well-being beyond consumption and developed better measures of social welfare indicators including poverty and inequality. In his powerful works, he introduced a different view of human economic agents having some intrinsic worth rather than just being rational utility maximizers. His notion of well-being also encompasses development of human potential by increasing the options available to individuals in any society. Sen asserted that when making normative evaluations about a 'valuable life', the focus should be on what people are 'able to be and to do', and not just on the material resources that they are able to consume.

These constitute the 'ends' of development (and economic growth is and should be evaluated in so far as it is an efficient and effective means to those ends). Such capabilities are defined as the freedom that people value (intrinsically) and have reason to value. As such, they cannot be imposed from an external source but nor are they fully relative to each person; rather the identification of key freedoms for any community is an appropriate topic for public discussion and debate. The capability approach is a multidimensional approach to poverty and well-being that provides an overarching picture of a society by moving beyond merely combining results from economic and social sectors to providing a picture of poverty and quality of life that is framed in terms of the valuable freedoms that people enjoy or lack.

In the last few decades, there have been a large number of studies that support the features of multidimensional welfare. In recent developments in literature on social welfare and its measurement, it can be seen that welfare is a multidimensional phenomenon. Traditional welfare economics holds that individuals are rational beings and free exchange will increase the well-being of these rational actors (Pressman and Summerfield, 2000). Concerning the measurement of general welfare, in the recent past there has been a debate on 'means' and 'ends' in the context of developing countries which has been dominated by Sen's (1992, 1996, 1999) capability approach. Given the criticism of using income as a proxy for human welfare, Sen proposed that human well-being should be measured directly by looking at people's capabilities and what they are able to do and be.

Alkire and Sarwar (2009) argue that a multidimensional approach moves away from the traditional unidimensional approach. They argue against focusing on a single dimension--in particular a monetary dimension--as a sufficient proxy for human welfare. The difficulties in using a single dimension such as income include debates on the extent to which income can translate into utility universally; the heterogeneity of people and contexts in converting income to utility; the role and contribution of the public sector; and political limitations and problems such as the effects of incomplete markets.

For example, income-based measures have been used for analyzing the state and level of poverty in developing countries including those in sub-Saharan Africa and South Asia for accounting for poverty. Several poverty indices are useful in estimating poverty levels and making inter-temporal and inter-country poverty comparisons. However, some also argue that we need to go beyond these money-metric measures and consider other poverty measurements. The first argument, a more practical one, relates to the fact that quality in the form of regularity and comparability of income/expenditure data is often poor in many developing countries, especially in sub-Saharan African ones that are generally regarded as showing the most poverty and in extreme forms. A second argument, more theoretical and methodological, concerns the multidimensional nature of well-being. Since Sen's seminal work (1976, 1985, 1992, 1995), well-being and poverty are now seen as multidimensional phenomena. Nowadays, there is a renewed interest in a multidimensional approach to poverty since relevant databases are increasingly available which enable comparative methodological and empirical analyses (Bataan, 2008).

In addition to his enormous contribution to literature, in Sen's influential work (1979, 1985, 1987) poverty has been increasingly recognized as a multidimensional phenomenon. Many factors other than income can provide important information on well-being and poverty such as the state of health, the level of education, ownership of assets, and access to basic services. Hence, it is not enough to look only at income poverty, but we must also look at other additional attributes.

Like poverty, empowerment too is a multidimensional issue. Empowerment is complex and multidimensional by its very nature that makes its measurement more difficult. This is especially true in the context of agriculture, where the concept of empowerment is relatively new (Alkire et al., 2013). Even if empowerment is intrinsically enjoyed at the individual level, several existing indices of empowerment and gender are typically measured at the aggregate country level. As Kabeer (1999, 2011) argues, women's empowerment is a multidimensional and relational concept whose dimensions include resources for empowerment; agency or the ability to make choices, including in relation to one's gendered attitudes and beliefs; achievements in the political, economic, social and cultural realms; and the intergenerational transmission of resources and opportunities (Kabeer, 1999). Women's empowerment is contingent on social transformation across these inter-related domains (Kabeer, 2005) and it is also both an individual and a collective process (Eger et al., 2018; Kabeer, 2011). Empowerment involves claims on assets and resources, as well as control over beliefs, values, and attitudes (Cornwall, 2016).

2. Nexus Between Poverty, Food Security, Empowerment, and Development

Von Braun et al. (1999) state that increasing agricultural productivity, technology adoption rates, and household food security and nutrition can be achieved through improved agricultural practices, expansion of rural financial markets, increased capital and equipment ownership by rural households, and developing research and extension linkages among these sectors. Increased technology development and adoption can raise agricultural output thus improving a household's food intake. Improved food intake can also improve the functioning of the human body and lead to a healthy, normal life which will increase working efficiency and output (Muzari et al., 2012). However, increased technology adoption may result in high labor demands and less time available for other household activities by women, since they also engage in a bulk of activities like childcare and fuelwood and water collection (Kennedy and Bouis, 1993).

Food insecurity in SSA is characterized by widespread and chronic hunger and malnutrition as well as recurrent and acute food crises that make Africa a continent with the highest proportion of undernourished people (29 percent), compared to a 17 percent average for developing countries. Chronic hunger and malnutrition are common problems on the continent (UN, 2009; Wiggins, 2009). Over 70 percent of the food insecure population in Africa lives in rural areas. Smallholder farmers, the producers of over 90 percent of the continent's food supply, make up half of this population (Mwaniki, 2006). The rest of the food insecure population consists of the landless poor in rural areas and the urban poor who need to look for additional food through food aid or international donors.

Women and children are particularly vulnerable, but often overlooked. Women face many constraints in their quest to access and produce food in agriculture. Women in rural areas are the most vulnerable: Uthman and Aremo (2008) did a study covering 27 countries in SSA and showed that rural women were 68 percent more exposed to malnourishment than urban women. Yet, there has been a general "failure to recognize the roles, differences and inequities between men and women" in the agricultural development agenda (The World Bank, 2009).

Food security and hunger eradication are among the top priorities on the international agenda today in view of the impact of global economic crises, spikes in food prices, and climate change on agricultural productivity. Hence, gender inequalities in general and gender gaps in agriculture are important goals given the vital role that women smallholders play in household and community food and nutrition security. Rural poverty exists in many different forms and can be associated with food insecurity; poor access to basic infrastructure and productive assets; climate change and depleted natural resources; lack of economic opportunities and poor working conditions; gender inequalities; volatility of market prices; indebtedness and financial crises; lack of time; poor health; exclusion; and fragile and violent situations (International Fund for Agricultural Development (IFAD) (2015)).

Evidence shows that in economies higher gender equality in terms of both opportunities and benefits, contributes not only to higher economic growth but also to a better quality of life. Addressing gender inequalities and empowering women are vital for meeting the challenge of improving food and nutrition security and enabling poor rural people overcome poverty (IFAD, 2015). Agricultural growth is enhanced if women and men are both enabled to participate fully as economic actors. Development programs are more relevant and sustainable if both women and men can participate in rural institutions and express their own needs and priorities in decision-making forums.

However, despite increasing evidence that women's improved capabilities and welfare are strongly linked to poverty reduction and other improvements like infant mortality and child malnutrition gender inequalities continue to be inordinately large in the developing world.

At present, with few exceptions, rural women fare worse than rural men, and urban women and men. According to FAO (2011) if women have equal access to productive inputs, the yields from their farms will increase by 20-30 percent and total agricultural output by 2.5-4.0 percent in developing countries. In effect, this will reduce the number of hungry people globally by 12-17 percent, or equivalent to 100 million to 150 million people globally.

Women are major players in the agriculture sector, in household food and nutrition security, and in natural resource management (WB, FAO, and IFAD, 2009). Evidence also shows that women invest 10 times more of their earnings than men for their family's well-being in areas including child health, education, and nutrition (Duflo, 2012; Quisumbing 2003; Quisumbing and Hallman 2003; Quisumbing and Maluccio, 2000, 2003; Skoufias 2005). Women's empowerment thus has a direct impact on agricultural productivity and household food security (Harper et al., 2013; Sraboni et al., 2014), and as a result it remains at the core of agricultural research and outreach practices in developing countries (Gates, 2014). Thus, gender related policy interventions that improve women's status and reduce gender inequalities are expected to improve women and children's well-being owing to women's important role in childcare and managing complex household activities including food preparation.

Yet women have significantly less access to inputs, services, rural organizations, productive infrastructural assets, services, and technologies than men. As a result of a combination of social and cultural norms, as well as the structure of the services infrastructure, women in almost all rural societies face specific challenges in accessing productive inputs, land and natural resources, technologies, and produce markets. Empowering rural women and girls is an essential part of the solution to some of today's most serious global challenges, mainly food security, poverty reduction, and sustainable development (United Nations Economic and Social Council, 2011). At the same time, gender equality and women's empowerment are now recognized as being at the heart of achieving all the MDGs and not just MDG#3 on gender equality (UNDP, 2010).

In its general context women's empowerment has several dimensions including economic empowerments. From those dimensions poverty alleviation is directly linked to economic empowerment, in which it is the type of individual associated with empowerment plus the first step towards empowering women. It is acknowledged that women's empowerment is needed in relation to economic growth and sustainable poverty reduction. The concept of women's empowerment is also used for understanding the conditions of impoverished women and impoverished poor women.

Women's empowerment is also increasingly seen as a strategy for enhancing household food security and nutrition (Sraboni et al., 2014; Verhart et al., 2016). Empowerment is the process by which an individual acquires the capacity for self-determination, that is, of living the life that she or he has reason to value (Galiè et al., 2017; Kabeer, 1999; Sen, 1999). Scholars and development practitioners continue to strive to understand what determines the capacity for self-determination and identifying the key domains of empowerment for its assessment. The choice of which domains to focus on (for example, psychological, economic, and political) may depend, for example, on the local context or on the topic of analysis (Bayissa et al., 2018). In the context of empowerment and nutrition, studies have found that when women earn, child and household nutrition are more likely to improve than when men earn an income (Smith et al., 2003; United Nations Children's Fund, 2011).

However, the process through which women's empowerment influences household nutrition and food security is complex and it is difficult to understand its mechanisms. A study in Ghana found that women's empowerment was positively linked to the quality of child feeding practices while it was only weakly positively associated with child nutrition status (Malapit and Quisumbing, 2015a). Similarly, a study in South Africa showed that only certain domains of women's empowerment (influenced by socio-cultural factors that directly hindered agricultural production) had any effect on food security (Sharaunga et al., 2015).

Women in rural areas are producers of food, income earners, and caretakers of their households' food and nutrition security. Evidence shows that investments in women's empowerment related projects help in improving broader development outcomes including health, education, poverty reduction, reducing vulnerability to food insecurity, and economic growth (Quisumbing 2003; Quisumbing and Maluccio, 2000; Mayoux, 2006). Evidence also shows that empowering women in the agriculture sector can provide sustainable ways for them to feed themselves leading to greater income improvements from the surplus produced, which again makes them less vulnerable to both poverty and food insecurity. Thus, women's empowerment and economic development are closely related: in one direction, development alone can play a major role in driving down inequalities between men and women and in the other direction, empowering women can benefit development (see Figure 1).

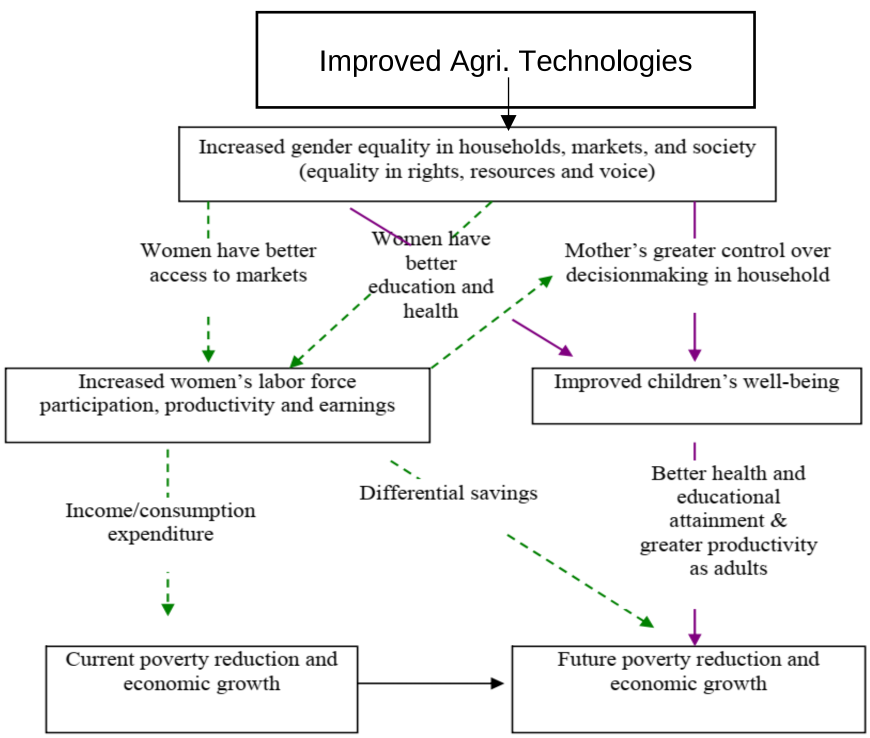

Figure 1. A conceptual framework linking gender equality and growth/poverty reduction
Source: Modified by the author based on Morrison et al. (2007).

Figure 1 shows the important inter-connection between women's empowerment, food security and nutrition, poverty, and economic growth. Gender related policy interventions that improve women's status and reduce gender inequalities can improve women and children's well-being thus contributing to the important role that women can play in children's education and health and nutrition. The process of empowering women in the agriculture sector to produce more food is one way of reducing vulnerability to poverty and food insecurity and increasing income and food consumption. Figure 1 also gives details of improvements in women's productivity and earnings and children's well-being for any given level of male earnings, which accelerate poverty reduction and economic growth, both contemporaneously and in the future.

In sum, the broader welfare indicators assessed in this thesis--multidimensional poverty, food security and child nutrition, and women's empowerment -- are strongly linked to each other and to general economic growth and development. A failure to account for the importance of one of these may lead to slow down and incomplete social and economic performance in general.

3. Agriculture Technologies and General Welfare in Developing Countries

Several empirical studies show that adoption of improved agricultural technologies and modern practices can affect households' welfare indicators like poverty, food security, productivity, employment, and income both directly and indirectly. Numerous studies in Africa show that adoption of improved agricultural technologies has the potential to affect welfare indicators in general. Studies that assess the impact of improved agricultural technologies on poverty in Africa include Asfaw et al. (2012) in Tanzania; Asfaw et al., (2012) in Tanzania and Ethiopia; Adekambi et al., (2009) in Benin; Faltermeier and Abdulai (2006) in Ghana; Hundie and Admassie (2016) in Ethiopia; Kassie et al. (2010) in Uganda; Khonje et al. (2015) in Zambia; and Zeng et al. (2015) in Ethiopia.

Studies conducted in Asia also show a similar significant impact of improved agricultural technologies on poverty. These studies include those by Mendola (2003, 2007) in Bangladesh; Sahu and Das (2016) in India; and Wu et al. (2010) in China. There are also some studies that evaluate the possible impact of modern agricultural technologies on poverty including the works of Becerril and Abdulai (2010) in Mexico.

When it comes to the impact of technologies on food security and nutrition, quite a few of the studies assess and find that technologies improve consumption (food security) and nutritional status of households in general. These studies include Di Falco et al. (2011); Ferede et al. (2003); Shiferaw et al. (2014); Tigabu and Gebeyehu (2018); and Zeng et al. (2014) all conducted in Ethiopia. Evidence also shows that the overall impact of technology adoption is almost the same (with very few exceptions) and context specific results show a positive impact of technologies on food security and nutrition.

There are a limited number of studies that connect agricultural technologies with women's empowerment; they have limited scope, consider a few dimensions, and the technologies are outside the impact of the evaluation context. Studies including those by Doss (2014); Gupta et al. (2017**);** Harper et al. (2013); Njuki et al. (2014); Sraboni et al. (2014). Malapit and

Quisumbing (2015); Sraboni and Quisumbing (2018) and Akter et al. (2017) highlight that women play a dominant role in the agriculture sector and their contributions are significant.

4. Issues Covered by This Thesis

This thesis presents deep assessments and empirical findings of the connection between improved agricultural technology adoption and multidimensional welfare indicators of poverty, food security, child nutrition, and women's empowerment in the context of program evaluation. The results from our studies highlight gaps in literature which this thesis fills with available data and using recent methods. Our results will help policymakers and development planners to better understand welfare indicators and develop appropriate development policies. The results also point out which improved agricultural technologies have a stronger effect on social welfare and related issues in Ethiopia's context.

4.1 Rationale, Motivation, and Research Questions

Despite a wide range of applied work on connections between agricultural technologies and general welfare, the extent of empirical measures of the potential and possible impact of agriculture technologies on welfare is less studied where the issues that are sensitive to the choice of methodology remain a matter of controversy. The big question here is: Why is the magnitude of regression coefficients different across studies? The first part of this thesis (Paper 1) narrows this gap by shedding shed light on the issue by performing a meta-analysis of literature on the welfare impact of improved agricultural technology adoption in Africa. To the best of our knowledge, among the existing studies only Ogundari and Bolarinwa's (2018) study considers this aspect though it is limited in coverage and considers studies published between 2001 and 2015 and discusses welfare in general terms. Hence, this thesis represents the first meta-analysis of the welfare impact of improved agricultural technology adoption in Africa. Our study contributes to existing research as it conducts a meta-analysis to test if the estimates obtained from the several studies vary as a result of differences in their contextual and methodological characteristics.

There is a lot of well-established empirical literature that shows that improved agricultural technologies reduce poverty using unidimensional income or expenditure-based measures of poverty. However, there are several factors in addition to income that can provide important information on well-being and poverty and hence, it is not enough to look only at income poverty as we also need to look at other additional attributes since there are several types of deprivations that money cannot reflect as poverty is a multidimensional phenomenon (Alkire and Foster, 2007, 2011a, 2011b, 2016; Alkire and Santos, 2014; Atkinson, 2003; Battiston et al., 2009; Bourguignon and Chakravarty, 2003; Maasoumi and Xu, 2015).

Many existing studies aim to contribute to the debate on the relative importance of 'direct' and 'indirect' effects of adopting agricultural technologies within poverty alleviation strategies. However, a large number of studies miss many important aspects of poor people's lives including the diverse ways in which technology directly or indirectly affects their livelihoods. Addressing issues of impact evaluation that most previous research puts less weight on this thesis considers endogeneity and the multidimensional nature of poverty. It further uses the multidimensional poverty approach to measure the impact of improved agricultural technologies and it also compares the results of multidimensional poverty with those of the standard unidimensional approach to poverty based on consumption measures and considers whether the inclusion of additional dimensions leads to a change in a household's poverty level from the standard-based approach.

Furthermore, over the last few decades several studies have been done in Ethiopia on adopting agricultural technologies and their associated welfare impacts. However, these studies are largely cross-sectional in nature and are based on similar datasets and focus on very limited aspects of agricultural technologies which may suffer from inefficient parameter estimates leading to inaccurate inferences of the models' parameters. In addition, causal linkages between agricultural technology adoption and child nutrition outcomes are rarely explored in existing impact evaluation literature.

Moreover, over time there has been a growing interest in the agriculture sector as an engine of growth and development, and in parallel the important role of women in the agriculture sector is also being recognized (Alkire et al., 2013; FAO, 2011). Women in rural societies are often responsible for managing complex household activities and pursuing multiple livelihood strategies. However, much less efforts have been made in developing indicators for measuring women's empowerment, for examining its relationship with various welfare outcomes or indicators, and effectively monitoring the impact of interventions in agriculture related sectors for empowering girls and women. Further, the complex and multidimensional nature of empowerment makes its measurement more difficult, and this is especially true in the context of agriculture, where the concept is relatively new. In addition, most available indicators are not appropriate for the agriculture sector.

Similarly, the impact of agriculture technology adoption on women's empowerment has not been studied in the program evaluation context and the issue of women's empowerment in agriculture is less studied. Existing literature focuses on 'women's empowerment in agriculture' but not on causal inferences (Akter et al., 2017; Malapit and Quisumbing, 2015; Sraboni et al., 2014; Sraboni and Quisumbing, 2018). To the best of our knowledge, there are gaps in literature on the dimensions of women's empowerment in agriculture which drive the process of empowerment due to the adoption of improved agricultural technologies.

Therefore, given these limitations in methodologies, data types, and location specific studies this thesis addresses the following major research questions to fill this gap in literature:

- Why do researchers come up with different findings when they assess the impact of improved agricultural technologies on welfare?
- Do improved agricultural technologies have the potential to affect households' multidimensional poverty status? If yes, under what circumstances?
- What impact do improve agricultural technologies have on household food security status?
- Are there any links between adoption of improved agricultural technologies and nutrition, particularly in the case of children?

- Do improved agricultural technologies matter for women's empowerment in rural Ethiopia? If so, which indicators and dimensions of women's empowerment are affected the most?

4.2 Objectives of the Thesis

The general objective of this thesis is exploring the impact of improved agricultural technologies on multidimensional poverty, food security and child nutrition, and women empowerment in rural Ethiopia. It also identifies why the findings differ across studies when assessing the impact of improved agricultural technologies on welfare.

Its specific objectives include:

- Assessing if differences in data type, estimation methods, and geographical location lead to different findings when dealing with the impact of improved agricultural technologies on welfare.
- Comparing the multidimensional poverty approach with the unidimensional approach to poverty based on consumption measures and considering whether the inclusion of additional dimensions leads to a change in a household's poverty level from the standard-based approach.
- Identifying the indicators and dimensions of women's empowerment that are most affected by the adoption of the technology under study.
- Exploring if adoption of improved technologies reduces the empowerment gap between men and women.

4.3 Methodological approaches and datasets

4.3.1 Common Challenges in Impact Evaluation and Estimation Strategies

The easiest method of examining the impact of adoption of improved technologies on welfare outcome indicators is by incorporating a binary variable equal to 1 if a farm household adopted new technology or 0 otherwise in the welfare equation and then estimating the impact using the ordinary least squares (OLS) method (Hausman,1978). The empirical challenge in impact evaluation using observational studies, however, is establishing a suitable counterfactual against which the impact can be measured because of self-selection and unobservable problems.

A program's impact assessment in a farm household setting is equivalent to assessing the causal effects of the program on a series of welfare indicators. In the impact evaluation problem, a person can be either in the treated or the control group, but not in both (Heckman et al., 1997). In the technology adoption framework, this means that the outcome variables of households that adopt technology would not be observed if they had not adopted the technology. Asfaw and Shiferaw (2010) state that analyzing the welfare influence of agricultural technologies is linked to two common challenges: 'unobserved heterogeneity and possible endogeneity problems' that need a correct formulation of the program's effects. Thus, the differences in the welfare outcome's variables between those farm households that did and those that did not adopt an improved technology could be due to unobserved heterogeneity. In such cases if the unobserved heterogeneity is not correctly controlled for, it may lead to inappropriate policy evaluations and implications.

Amare et al. (2012) and Asfaw et al. (2012) also state that adoption is not randomly distributed between the two groups of treated and not treated, instead households make their choices based on available factors and thus, the two groups may be systematically different. Therefore, possible self-selection due to observed and unobserved household characteristics makes an assessment of the real welfare impact of technology adoption based on observational data difficult as compared to experimental studies. If we fail to correctly account for this potential selection bias, it could lead to inconsistent estimates of the impact of technology adoption.

However, the decision to adopt or not is voluntary and is taken based on an individual's self-selection process. Farmers who have adopted technology may have systematically different characteristics compared to farmers who have not adopted the technology. The former may have decided to adopt the improved technology based on expected adoption benefits. In an experimental setting, this problem is addressed by randomly assigning adoption to treatment and control status and thus the welfare indicator's variables observed in the control households that do not adopt are taken as representative of what would have happened to the adopters if they had not adopted the technology.

Common econometric approaches for dealing with the selection bias include propensity score matching (PSM), generalized propensity score (GPS) matching methods, endogenous switching regression (ESR), treatment effects models (TE) of different types, sample-selection models, instrumental variable (IV) approaches, correlated random effects (CRE), fixed-effects (FE) models, the difference-in-difference (DID) method, economic surplus, and double hurdle. The choice of these approaches depends on factors like the type of data, objective, and theory but common to all is that each method has its own strengths and weaknesses. For example, PSM only controls for observed heterogeneity while IV can control for unobserved heterogeneity. Thus, the disadvantage of using a single model is that the estimates may not be robust enough because each model has its own limitations which cannot be individually corrected. So, a better way of studying impact evaluation is by using some combination of these methods to check the robustness of the results and for minimizing biases.

4.3.2 The Conceptual /Theoretical Modeling Framework

4.3.2.1 Agricultural Technologies and Adoption Behaviors of Farm Households

Adoption of agricultural technologies is influenced by several inter-related components within the decision-taking environment in which farmers operate. Thus, given that technology uptake is a complex non-linear process influenced by multiple factors, the use of a single theory for analyzing decision-making will not provide a full picture of the adoption process. Feder et al. (1985) identified lack of credit, limited access to information, inadequate farm size, insufficient human capital, tenure arrangements, absence of adequate farm equipment, chaotic supply of complementary inputs, and inappropriate transportation infrastructure as key constraints in the rapid adoption of innovations in less developed countries. However, not all factors are equally important in different areas and for farmers having different socioeconomic situations. Farmers' socioeconomic conditions are the most cited factor influencing technology adoption. The variables most included in this category are age, education, household size, landholding size, and other factors that indicate the wealth status of farmers (see Figure 2).

Farmers' decisions to adopt improved agricultural innovations can be explained based on three major conceptual models: the innovation-diffusion model, the economic constraints model, and the users' perception model (Adcsina and Zinnah, 1993: 298, cited in Ferede et al., 2003). The innovation diffusion model which is based on Rogers' (1962) work contends that the decision to adopt a new technology is determined by access to information about that technology. In this model, the technology is assumed to be appropriate so the use of effective communication such as extension, media, on-farm trials, and field demonstrations enhance the adoption of a new agricultural technology (Feder et al., 1985: 275).

The economic constraints model argues that the distribution of resource endowments determines the pattern of technology adoption by potential users. Economic factors such as access to land, labor, and capital could significantly affect the decision to adopt new agricultural innovations (Feder et al., 1985: 271-278).

The third conceptual model, farmers' perception model (Fliegel and Kivlin, 1966: 202-205; Kivlin and Fliegel, 1967: 90) shows that farmers' perceptions of an innovation attribute and shape their adoption behavior. According to this model, farmers have subjective preferences for specific characteristics and these perceptions could greatly influence their adoption decisions. Figure 1shows the conceptual framework of farm technology adoption based on these theories and common phenomena in farm household behavior.

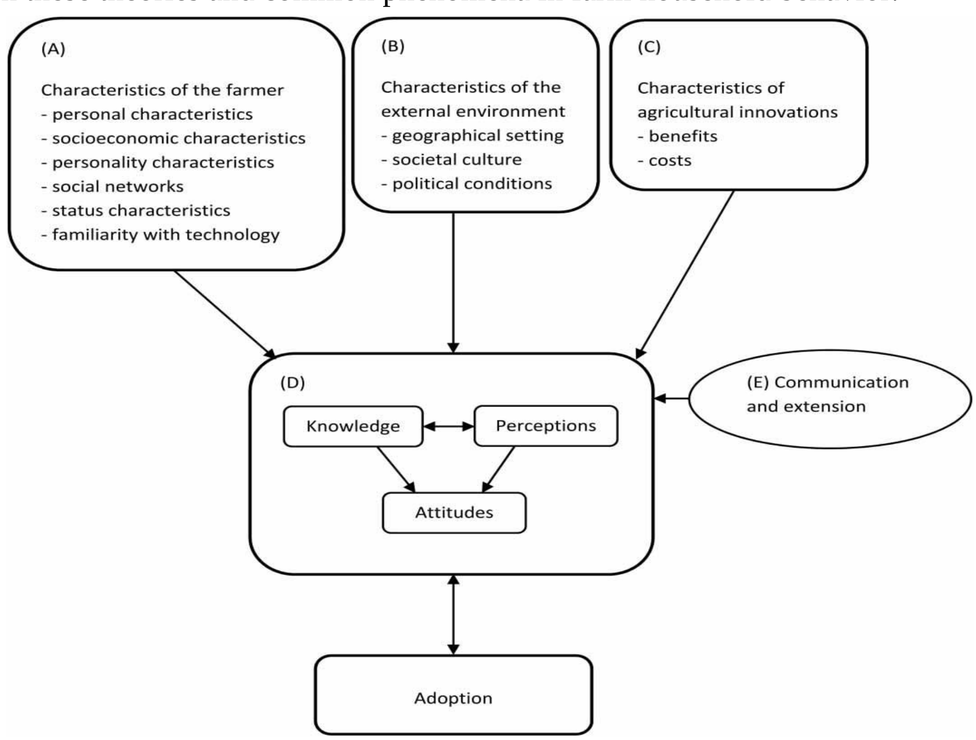

Figure 2: Conceptual Framework of farm technology adoption.
Source: Adapted from Meijer et al. (2015)

Theoretically, we can model the adoption of available technologies under the assumption that farmers choose between the available technologies based on functions subject to some constraints. We assume here that farmers are net benefit maximizers[1] of technology in the decision-making process. Farmers are therefore assumed to choose a technology that provides maximum net benefits. Under this assumption and following Abdulai and Huffman (2014); Rahm and Huffman (1984); Di Falco et al. (2011); and Shiferaw et al. (2014) let us represent the net benefit for farmer i deriving from adopting the technology as Y_{iA} and the net benefit from non-adoption represented as Y_{iN}, with net benefits representing the outcome variables (welfare indicators in our case).

Now the two-regimes net benefit equation can be specified as:

$(1a) \qquad Y_{iA} = \alpha_A X_i + \eta_i A$ and

$(1b) \qquad Y_{iN} = \alpha_N X_i + \eta_i \mathrm{N}$

where X_i is a vector that represents demographic, institutional, and fixed factors; farm and household characteristics α_A and α_N are vectors of parameters; and $\eta_i A$ and $\eta_i N$ are identically and independently distributed(iid) error terms. The farmer will normally choose a technology if the net benefits obtained from the adoption are higher than those obtained by not adopting the technology.

Let the difference between net benefits (Y_{iA}) and (Y_{iN}) of the technology be *W* such that the net benefits maximizing farm household *i* will choose to adopt the technology if the benefits gained from adopting are greater than those of not adopting the specified technology which is given by($W^* = Y_{iA} - Y_{iN} > 0$). However, the two net benefits are unobservable and thus they can be expressed as a function of observable components in the latent variables model (which is not observed but can be expressed as a function of the observed characteristics) as:

$$(2) \qquad W_i^* = \psi \mathrm{Z}_i + \varepsilon_i, with \;\; W_i = \begin{cases} 1 & if \; W_i^* > 0 \\ 0 & otherwise \end{cases}$$

where *W* is a binary 0 or 1 dummy variable for the use of a new technology; *W*=1 if the technology is adopted and W = 0 otherwise. ψ is a vector of the parameters to be estimated and Z is a vector that represents household characteristics. Thus, a farmer adopts the technology only if its perceived net benefits are positive. In this thesis, all the chapters are modeled based on this conceptual and theoretical setting except the chapter that deals with the meta-analysis.

4.3.3 Empirical Methodologies

This thesis uses different econometric methodologies in the papers depending on the subject being studied.

The objective of Paper 1 is explaining the factor(s) behind the variations in the results across studies that target the welfare impact of improved agriculture technology adoption in the African context using 52 sample studies in Africa. This paper does a meta-regression analysis of income or expenditure, food security, and poverty as outcome variables to capture

[1] In the standard household theory, this means that a farm household behaves in the utility maximizing framework.

the reported impact of adopting improved agricultural technologies on welfare in Africa from the primary studies. In doing so, it estimates an equation for integrating the empirical results across different studies. The study also tests for publication bias.

Paper 2 employs the two common and relevant program evaluation techniques, PSM and ESR methods depending on the cross-sectional Ethiopian Socioeconomic Survey (ESS)[2] data, which is a collaborative project between the Central Statistical Agency (CSA) and the World Bank's Living Standards Measurement Survey (WB-LSMS) -Wave 3 collected in 2015. The differences in farm households in the decision to adopt or not to adopt new agricultural technologies and unobservable characteristics of farmer households are accounted for by estimating the full information maximum likelihood (FIML) estimation method while a non-parametric regression method, PSM is also used to assess the robustness of the results. We also employed the Alkire and Foster (AF, 2007, 2011a) counting approach to measure the multidimensional poverty index.

Paper 3 takes advantage of the panel data dimension of the two waves of ESS data, rounds 2 and 3 (collected in 2013 and 2015) to examine the impact of improved agricultural technologies on food security and child nutrition in rural Ethiopia. This paper uses three different estimation approaches. The first empirical approach is the two-way fixed-effects (FE) error component structure method which is a more flexible approach that allows us to estimate treatment effects considering different adoption times. We use the fixed-effects model to eliminate the effects of observable and unobserved household heterogeneity but fixed over time, as a source of bias in estimates of the technologies' impact. Commonly the fixed effects error structure only incorporates the potential influence of time-invariant unobservable factors.

We also complement the analysis by employing other methods that take into account the selection biases both from observable and unobserved factors and address some limitations of the FE approach. These methods include PSM and endogenous treatment effects (ETE) models. PSM is employed to assess the robustness of the results and is one of the most widely used non-parametric estimation techniques of impact evaluation while ETE is used to account for selection biases on households' technology adoption decisions, especially the unobserved and time-variant components.

Finally, Paper 4 is based on the complete panel data of ESS-Waves 1-3. The study employs the DID with the two-ways fixed-effects method that can control for systematic differences between the households in the treated and control groups but DID is less efficient when the two groups do not share similar profiles; for such cases, we also use the PSM technique to compare the outcomes between households with similar probabilities of being treated given a set of characteristics. To measure women's empowerment, we use the Abbreviated Women's Empowerment in Agriculture Index (A-WEAI) and its two components, the five domains of empowerment (5DE), and the Gender Parity Index (GPI).

[2] The Ethiopian Socioeconomic Survey (ESS) and the World Bank's Living Standards Measurement Survey (WB-LSMS) are used interchangeably in this thesis as they belong to the same dataset.

Note also that improved agricultural technologies considered in these papers are of different types. In Paper 2 improved technology refers to a combined adoption of row planting methods with chemical fertilizers while in Paper 3 we considered three sets of different agricultural technologies: the recommended planting method (row planting), using high yielding varieties of seeds (HYVs), and chemical fertilizers used separately. In the last paper, improved technology is application of chemical fertilizers with extension services at the farm level.

4.3.4 Data sources and Limitations

The first part of the thesis, the meta-analysis, is based on a sample of 52 improved technology adoption studies focusing on the agriculture sector in Africa. The next three papers use secondary data collected from the Ethiopian Socioeconomic Survey (ESS) data during different waves. Even though these chapters use the same dataset, they use different portions of the data depending on the objectives and technology types.

The second paper, 'Impacts of Improved Agricultural Technology Adoption on Multidimensional Poverty in Rural Ethiopia', uses the cross-sectional component of the ESS dataset -Wave 3 collected in 2015.The data targeted the rural areas and small and medium towns in the country. The survey covered around 4,954 households drawn from the nine regional states and two city administrations. Households from both small and medium towns were excluded because of non-applicability of agricultural technology adoption after which the sample size became 3,727. After adjusting and accounting for missing variables and values the final sample used in the current study was 2,752 households across the regions of the country. The dataset has good qualities such that it contains information regarding income or consumption expenditure, so we were able to assess how the inclusion of additional dimensions of poverty affected our measurement of poverty in the MPI approach as compared to the monetary approach.

The third paper, 'Do Improved Agricultural Technologies Affect Household Food Security and Child Nutrition in the Case of Rural Ethiopia', using the last two waves (Waves 2 and 3) of the ESS data collected in 2013 and 2015. The two surveys are nationally representative of rural and small towns in Ethiopia. The survey covered around 5,262 and 4,954 households drawn from the nine regional states and two city administrations in Waves 2 and 3 respectively. The study considered three types of agricultural technologies and improved practices -- row planting or recommended spacing, HYVs, and chemical fertilizers. Separate data was organized for each type of technology for simplicity and ease of analysis. After controlling and accounting for missing observations and non-applicable households, the sample size for row planting technology was 3,875 while 5,295 households were taken for the HYVs category, and 5,806 households were considered for chemical fertilizers.

The last paper, 'Agricultural Technologies and Women's Empowerment in Rural Ethiopia: Do Improved Agricultural Technologies Matter?' is based on the entire ESS panel data. The survey data has good qualities like it covers different household members including males and females in the same household. We restrict the sample to rural households to ensure that women's A-WEAI indicators among urban households that are not engaged in agricultural production are not misinterpreted as low empowerment achievements.

The original WEAI includes five domains and the indicator, but our study uses A-WEAI which still retains the five domains of empowerment, and the ten indicators of WEAI are reduced to six. To measure disempowerment scores, we first identified the inadequacy achievements of each person in the five domains (production, resources, income, leadership, and time). Next, we calculated each person's inadequacy score by taking a weighted sum of the inadequacies experienced. The final sample used was 3,382 (each sex being 1,691) for each wave which added to a sample of 10,146 individuals.

Though the dataset has some good qualities and covers a wide range of issues, it has some shortcomings in some areas or variables and measurements. In Paper 2 the focus of the study is on the impact of improved agricultural technologies on multiple rural dimensions of poverty. Unfortunately, the data does not contain information on the health dimension's attributes of child mortality and nutrition. To address this problem, we used parental consultations and physical or mental disability indicators to represent the health dimension. Similarly, there is no information regarding one indicator of education -- child school attendance -- in the dataset so we used reading and writing abilities of any household member as a possible proxy.

In Paper 3 one of the challenges in relation to the data was absence of information on the child nutrition indicator. We proposed to use either anthropometric measurement indicators like height and weight and circumference and length of various body regions or the body mass index (BMI) but none of this information was included in the survey. One possible and available option was using the average food intake per day per child and its variety as a possible proxy for child nutrition.

5. Outline of the Thesis

This thesis covers broad issues related to an assessment of connections between adoption of modern agricultural technologies and improved practices and households' welfare in the program evaluation context. It incorporates a comprehensive meta-analysis and the impact of various agricultural technologies on multidimensional welfare indicators like poverty, food security, child nutrition, and women's empowerment in the agriculture sector.

The thesis is organized into five chapters. The first chapter provides a detailed background of the study; rationale, motivation and research questions; objectives; and the methodologies used, and data type and issues related to welfare and its measurements. It also shows the gaps in literature and helps in filling the observed gaps.

The second chapter (Paper 1) does a meta-analysis of improved agricultural technologies and their impact on welfare in Africa conducted on a sample of 52 studies which were assumed to help us find the gaps in literature. This paper was presented at a seminar organized by the Jonkoping International Business School (JIBS) in August 2018, Sweden and on the 15th Annual Conference of The Ethiopian Economics Association held on 19-21 July, 2018 in Addis Ababa.

The third chapter (Paper 2) examines the impact of adopting improved agricultural technologies on multidimensional poverty by employing propensity score matching and endogenous switching regression methods for measuring the causal inference and the Alkire and Foster counting approach for measuring the multidimensional poverty index.

An earlier version of this paper was published as Habtewold (2018), 'Adoption and Impacts of Improved Agricultural Technologies on Rural poverty', in A. Heshmati and H. Yoon (eds), *Economic Growth and Development in Ethiopia. Perspectives on Development in the Middle East and North Africa (MENA) Region*. Singapore: Springer, Chapter 2, pp. 13-38, and it was also presented at a seminar organized by the Jonkoping International Business School (JIBS) in August 2018. The paper was also accepted for a poster presentation at the 33rd European Federation of Food Science and Technology (EFFoST) International Conference hosted in the Postillion Convention Centre, WTC Rotterdam, the Netherlands, November 12-14, 2019.

The fourth chapter (Paper 3) relates improved agricultural technologies to food security and child nutrition in Ethiopia. It was presented at a seminar organized by the Jonkoping International Business School (JIBS) in January 2019 and was also presented at the 4th Annual Eastern African Business and Economics Watch (4th EABEW, 2019), an international conference organized in collaboration between the University of Rwanda and JIBS, (June 12-14, 2019), Kigali, Rwanda.

The last paper links improved agricultural technologies to women's empowerment in the context of impact evaluation relying on panel data. It applies the Abbreviated Women's Empowerment in Agriculture Index and its two components, five domains of empowerment, and the Gender Parity Index to measure empowerment. It was presented at a seminar organized by JIBS in October 2019.

6. Contributions of the thesis

This thesis contributes to the growing literature on program evaluation in Ethiopia. Existing literature is limited in scope and the type of technologies it discusses. Specifically, the thesis makes the following contributions to existing literature:

- The meta-analysis represents the first study of the welfare impact of improved agricultural technology adoption in Africa. This paper contributes to existing research as it conducts a meta-analysis to test if the estimates obtained from the various studies vary as a result of differences in their contextual and methodological characteristics.
- It was also observed that a multidimensional poverty approach for measuring the impact of improved agricultural technologies has not been explored so far in the country, which makes this study well-placed and timely for policymaking and related interventions.
- In literature on agriculture technologies and their impact on welfare, several studies have use single econometric models. The problem with using a single model is that the estimates may not be robust enough because each model has its own limitations. Unlike most previous studies, this paper is novel as it uses recent (2011-15) ESS datasets and uses combinations of two or more impact evaluation methods to check the robustness of the results and minimizing biases.

- The study also incorporates the newly introduced measure of women's empowerment in the agriculture sector (A-WEAI) and its two components, 5DE and GPI, and connects this to the program evaluation study. We hope that this new methodology will help promote further development of impact evaluation settings in issues concerning women's empowerment in the agriculture sector.
- The study also considers different sets of modern agricultural technologies and improved practices. So far literature has concentrated on studying single agricultural technologies.
- Overall, all the papers present a consistent and coherent story. Improved agricultural technologies are beneficial in many different dimensions. Our results are relevant and though the empirical findings are based on a country specific dataset, the lessons learnt are of global importance.

7. Summary and Conclusion the Thesis

This section discusses the main findings and policy implications of the papers in the order in which they appear in the thesis. The thesis shows the importance of improved agricultural technologies and practices on multidimensional welfare in rural Ethiopia. The papers are held together by concepts and associated theories (as discussed in Part 2 of this introductory chapter; also see Figure 1) for showing the linkages between multidimensional welfare indicators and an analysis of agricultural technologies' impact in the program evaluation context.

The first paper, 'A Meta-analysis of Improved Agricultural Technologies and their Impact on Welfare in Africa', assesses the basic factors behind the large variations in the results that previous studies have arrived at. Through our meta-analysis of a relatively large sample of studies we identify important factors that influence the welfare impact of agricultural technology adoption in Africa.

The results of the first outcome variable (output/expenditure) show that studies that used cross-sectional data showed significantly lower percentage points of output or expenditure estimates than those using panel or time series data, and studies that used data from East African countries in their analyses reported higher output or expenditure values compared to the other regions. In the case of food security, our meta-analysis showed that the year of the study and studies that used theories in their original work reported relatively higher and positive percentage gains in food security as a result of improved technology adoption in the agriculture sector. It was also observed that studies that did their analyses in East African countries and studies with larger sample sizes reported lower food security.

Finally, the results of the third outcome variable, poverty index, showed that all the significant variables -- year of the study, data type, sample size, journal type, and regions studied -- reported significantly lower poverty index reduction in percentage points while only the model type variable reported significantly higher poverty index reduction. Our meta-regression analysis also showed that there was no evidence of publication bias in the first and third models while in the second model the test's results indicate that publication bias existed.

The second paper connects the multidimensional poverty methodology to the impact evaluation technique in the agriculture sector. The study uses consumption expenditure as one indicator of households' poverty status and the results of the poverty analysis show that about 42 percent of the households in the country were poor. Using the relative poverty line, the median value of consumption expenditure, about 47 percent of the households were below the poverty line. When it comes to the adoption status of households, households that used the technology were slightly better-off than non-users implying that the specified technology improved adopters' welfare. The empirical results also showed that average welfare gains of the adopted technology ranged from Birr 152 to Birr 203 when consumption expenditure was an outcome, while the reduction in poverty ranged between 0.20 - 0.31 percentage points.

The second study also discusses the measurement of multidimensionality of poverty and status of households across different categories. When each dimension was considered, the results showed that people were the most deprived in the education dimension (41.8 percent) followed by the standard of living dimension (34.6 percent). Indicator-wise, people were the most deprived in terms of years of schooling (24.6 percent) while they were less deprived in access to clean water (3.2 percent). It was also found that the adoption of technology reduced the overall deprivation in the range of 2.0-3.0 percent. Based on these analyses, we found that the living standard component of MPI drove the change in households' poverty status indicating a reduction in living standards' deprivation between 1.6-2.2 percent. A regional comparison also showed that there was high reduction in deprivation in Amhara region (7.1 percent) followed by Oromiya (5.3 percent). The results also showed that the impact was significantly higher in the severely deprived households (whose deprivation score was greater than 0.50). Finally, we noted that the inclusion of additional dimensions of poverty improved our measurement of poverty.

The results of this study showed that the extent of multidimensional poverty was very high, and the impact of technology varied across regions and by sex which requires concerted policy interventions. The results also showed that there were large regional variations in poverty status. Policymakers should consider regional variations, community realities, and households' characteristics to fight poverty. At the country level, this may require a revision of the national poverty reduction strategies to incorporate the multidimensional aspects of deprivation and considering appropriate agricultural technologies that most affect multidimensional poverty and its components.

The third paper considers three different agricultural technologies: row planting, HYVs, and chemical fertilizers and relates improved agricultural technologies to food security and child nutrition. The findings showed that for row planting, the average increase in per capita consumption expenditure using the FE models was higher by about 756 Birr for adopters as compared to non-adopters. Our study also showed that children in the technology adopter household group had increased food intake per day of about 6 percent compared to children in the non-adopter group. Similar results were obtained using PSM, where the overall average gain of per capita consumption ranged from 633 to 750 Birr under the four algorithms; similar results were obtained using the ETE approach as well.

The study also investigated the impact of HYVs on the welfare of rural households and the results showed that adopting improved varieties resulted in highly increased per capita consumption expenditures among the adopters. The results from all the three estimation methods showed that per capita consumption expenditures among the adopters of HYVs increased in the range of 532 to 707 Birr. The estimated results for child nutrition also suggest that on average daily food intake for children in households that adopted HYVs increased in the range of 7 to 8 percent. Similarly, when it comes to fertilizer adoption, both per capita consumption and average daily food intake for children of adopter households increased significantly.

The positive and significant impact of improved agricultural technologies on food security and child nutrition due to adoption of these three technologies suggests the need for continued and broad public and private investments in agricultural research and different technologies to address important development challenges; the results also showed that policy support for improving extension efforts and access to seeds and market outlets that simulate adoption of improved agricultural technologies are needed.

A one-time trial or use of an agricultural technology can hardly change livelihoods. This reinforces the need for using technologies on a continuous basis. Given that farmers' variety-attribute preferences determine both their propensity to use improved varieties and the chances of using them successfully, breeding should satisfy the demands of different farm household types classified according to resource skills, endowments, preferences, and constraints.

The last paper links improved agricultural technologies to women's empowerment. Very few studies have tried to measure women's empowerment in agriculture and incorporate it in program evaluation settings as its complex and multidimensional nature make these attempts difficult and hence there are limited efforts in the area of empowerment and gender parity/disparity issues. The descriptive statistics' results show that women's disempowerment was almost similar to that of men such that about 91.27 percent of women and 90.32 percent of men were disempowered in the five domains of empowerment (5DE) where the total sample's achievement score in 5DE was 0.46 while GPI was 0.91, and the A-WEAI was 0.50. On the other hand, parity was enjoyed by 58.80 percent of the women. Women in the adopter group were significantly more empowered in 5DE and enjoyed more gender parity as compared to women in the non-adopter group.

Our empirical results also show that adoption led to a more than 4 percent increase in 5DE for the total sample, while sex-wise the increase was more than 5 percent for females and around 4 percent for males. Again, in computing the impact of technology on each component of 5DE, adoption did not affect any of the first four components, except time allocation where adoption led to a 3.50 percent increase in time allocation empowerment. In computing the impact of technology on EG, the results are mixed. Finally, a regional disaggregation of the impact revealed that adoption did not improve women's empowerment throughout all regions. The impact was more powerful in regions like Amhara and Oromia while the impact was negative and significant in regions like Benishangul and SNNP. However, the aggregate impact was positive and significant indicating that technology had the power to improve empowerment in 5DE. Last, we observed that the change in A-WEAI was derived by 5DE as compared to GPI.

Even though we found a strong impact of adoption on 5DE, the value of this component was among the lowest in SSA. This needs policy interventions that increase A-WEAI. The strong relationship between the impact of adopting a specified technology and 5DE levels in this study suggests that empowerment of women could be a pathway for reducing poverty and vulnerability to food insecurity. It was, however, observed that more that 75 percent of the women did not have access to credit and a significant number of women did not have control over use of income. This too needs policy support for improving access to and method of using credit in their households and ensuring women's ability to take decisions related to incomes. Men and women can take decisions to differing degrees in the same household. In such cases creating awareness about joint decision making and cooperation on issues in their households will increase the impact of technology on the existing gender gap. In Ethiopia, social norms are also an important determinant of participation in economic and social activities (and need to be considered), which in turn affect women's empowerment directly or indirectly.

References

Abdulai, A., & Huffman, W.E. (2014). The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Economics,* 90 (1), 26–43.

Adekambi, S. A., Diagne, A., Simtowe, F., & Biaou, G. (2009). The Impact of Agricultural Technology Adoption on Poverty: The Case of, NERICA Rice Varieties in Benin. Contributed paper prepared for presentation at the International Association of Agricultural Economists' conference, Beijing, China, August 16-22, 2009.

AfDB (2012). *Malawi Interim Country Strategy paper 2011-2012*. Tunis: African Development Bank.

Akter, S., Rutsaert, P., Luis, J., Htwe, N.M., San, S.S., Raharjo, B., & Pustika, A. (2017). Women's empowerment and gender equity in agriculture: A different perspective from Southeast Asia. *Food Policy,* 69, 270–279.

Alkire, S., & Foster, J. (2007). Counting and Multidimensional Poverty Measurement. OPHI Working Paper 7, Oxford University.

Alkire, S., & Foster, J. (2011a). Counting and Multidimensional Poverty Measurement. *Journal of Public Economics*, 95(7–8), 476–487.

Alkire, S., & Foster, J. (2011b). Understandings and Misunderstandings of Multidimensional Poverty Measurement. *Journal of Economic Inequality*, 9(2), 289–314.

Alkire, S., & Foster, J. (2016). Dimensional and Distributional Contributions to Multidimensional Poverty. *OPHI Working Paper 100, Oxford Poverty and Human Development Initiative,* University of Oxford.

Alkire, S., & Sarwar, M. B. (2009). Multidimensional Measures of Poverty and Well-being. OPHI Report Working Paper of Oxford Department of International Development, Queen Elizabeth House University of Oxford.

Alkire, S., & Santos, M.E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development*, 59, 251–274.

Alkire, S., Meinzen-Dick, R.S., Peterman, A., Quisumbing, A.R., Seymour, G., & Vaz, A. (2013). The Women's Empowerment in Agriculture Index. *World Development,* 52, 71–91.

Amare, M., Asfaw, S., & Shiferaw, B. (2012). Welfare impacts of maize–pigeon pea intensification in Tanzania. *Agricultural Economics*, 43(1), 27–43.

Asfaw, S., & Shiferaw, B. (2010). Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Poster presented at the 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19 – 23, 2010

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012a). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy,* 37(3), 283–295.

Asfaw, S., Kassie, M., Simtowe, F., & Leslie, L. (2012b). Poverty Reduction Effects of Agricultural Technology: A Micro-evidence from Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Atkinson, A.B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality*, 1, 51–65.

Atkinson, A.B., & Bourguignon, F. (1982). The Comparison of Multidimensional Distributions of Economic Status. *Review of Economic Studies*, 49, 183–201.

Baiphethi, M. N., & Jacobs, P. J. (2009). The contribution of subsistence farming to food security in South Africa. *Agrekon*, 48, 459–482.

Bataan, Y. M. (2008). Multidimensional Measurement of Poverty in Sub-Saharan Africa. OPHI Working Paper 13, Oxford University, August 2008.

Battiston, D., Cruces, G., Lopez-Calva, L. F., Lugo, M. A., & Santos, M. E. (2013). Income and Beyond: Multidimensional Poverty in six Latin American countries. *OPHI Working Paper 17, Oxford Poverty and Human Development Initiative,* University of Oxford.

Bayissa, F.W., Smits, J., & Ruben, R., (2018). The multidimensional nature of women's empowerment: beyond the economic approach. *Journal of International Development*, 690, 661–690.

Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: a propensity scores matching approach. *World Development, 38*(7), 1024-1035.

Bourguignon, F., & Chakravarty, S.R. (2003). The Measurement of Multidimensional Poverty. *Journal of Economic Inequality*, 1, 25–49.

Cornwall, A. (2016). Women's empowerment: What works. *Journal of International Development*, 28, 342–359.
Deathier, J.J, & Effenberger, A. (2012). Agriculture and development: A brief review of the literature. *Economic system*, 36(2), 173-336.
Di Falco, S., Veronesi, M., & Yesuf, M., (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93 (3), 829–846.
Doss, C.R (2014). If women hold up half the sky, how much of the world's food do they produce? in A.R. Quisumbing, R. Meinzen-Dick, T.L. Raney, A. Croppenstedt J. A. Behrman, and A. Peterman (eds), *Gender in agriculture: Closing the knowledge gap* (pp. 69– 88). The Netherlands: Springer.
Duflo, E., (2012). Women empowerment and economic development. *Journal of Economic Literature*, 50, 1051–1079.
Eger, C., Miller, G., & Scarles, C. (2018). Gender and capacity building: A multilayered study of empowerment. *World Development*, 106, 207–219.
Faltermeier, L., & Abdulai, A. (2006). The Adoption of Water Conservation and Intensification Technologies and Farm Income: A Propensity Score Analysis for Rice Farmers in Northern Ghana, Annual Meeting, July 27-29, Orlando, Florida, American Agricultural Economics Association.
FAO (Food and Agriculture Organization of the United Nations) (2011a). *The state of food and agriculture 2010–2011. Women in agriculture: Closing the gender gap for development.* Rome: Food and Agriculture Organization of the United Nations.
FAO (Food and Agriculture Organization of the United Nations) (2015). *The state of food security in the World*. Rome: Food and Agriculture Organization of the United Nations.
FAO (Food and Agriculture Organization of the United Nations) (2017). *The future of food and agriculture – Trends and challenges*. Rome: Food and Agriculture Organization of the United Nations.
Feder, G., Just, R.E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: a survey. *Economic Development and Cultural Change*, 33(2), 255-298.
Feleke, S., & Zegeye, T. (2006). Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy*, 31, 442–457.
Ferede, S., Ayele, G., & Teklewold, H. (2003). Impact of Technology on Households Food Security, in Tef and Wheat Farming Systems of Moretna_Jiruworeda. Ethiopian Agricultural Research Organization (EARO), Research Report No.48.
Fliegel, F.C., & Kivlin, J.E. (1966b). Farmers' perceptions of farm practice attributes. *Rural Sociology*, 31(2), 197-206.
Galiè, A., Jiggins, T., Struik, P.C., Grando, S., & Ceccarelli, S. (2017). Women's empowerment through seed improvement and seed governance: Evidence from participatory barley breeding in pre-war Syria. *NJAS - Wageningen Journal of Life Sciences* 81, 1–8.

Gates, M.F. (2014). Putting women and girls at the center of development. *Science* 345, 1273–1275.
Gupta, S., Pingali, P.L., & Pinstrup-Andersen, P. (2017). Women's empowerment in Indian agriculture: does market orientation of farming systems matter? *Food security*, 9(6), 1447–1463.
Habtewold, T.M. (2018). "Adoption and Impacts of Improved Agricultural Technologies on Rural poverty", in A. Heshmati and H. Yoon (eds) *Economic Growth and Development in Ethiopia. Perspectives on Development in the Middle East and North Africa (MENA) Region* (pp. 13-35*)*. Springer, Singapore.
Hagos, F., Jayasinghe, G., Awulachew, S.B., Loulseged, M., & Yilma, A.D. (2012). Agricultural water management and poverty in Ethiopia. *The Journal of the International association of Agricultural Economics,* 43, 99–111.
Harper, S., Zeller, D., Hauzer, M., Pauly, D., & Sumaila, U.R. (2013). Women and fisheries: Contribution to food security and local economies. *Marine Policy*, 39, 56–63.
Hausman, J.A. (1978). Specification tests in econometrics. *Econometrica,* 46, 1251-1272.
Heckman, J., Ichimura, H., & Todd, P. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program. *Review of Economic Studies,* 64, 605-654.
Hundie, B., & Admassie, A. (2016). "Potential Impacts of Yield-Increasing Crop Technologies on Productivity and Poverty in two Districts of Ethiopia", in F. Gatzweiler and J. von Braun (eds), *Technological and Institutional Innovations for Marginalized Smallholders in Agricultural Development.* Springer International Publishing (pp. 397-421).
International Fund for Agricultural Development (IFAD) (2015). *Poverty targeting, gender equality and empowerment. Gender, targeting and social inclusion. Investing in poor people, Rome, Italy*
Kabeer, N. (1999). Resources, agency, achievements: Reflections on the measurement of women's empowerment. *Development and Change*, 30, 435–464.
Kabeer, N. (2005). Gender equality and women's empowerment: A critical analysis of the third millennium development goal 1. *Gender and Development*, 13(1), 13–24.
Kabeer, N. (2011). Between affiliation and autonomy: Navigating pathways of women's empowerment and gender justice in rural Bangladesh. *Development and Change*, 42(2), 499–528.
Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda. *Environment for Development Discussion Paper-Resources for the Future (RFF)*, (10-11).
Kennedy, E.T., & Bouis, H. E. (1993). Linkages between Agriculture and Nutrition: *Implications for Policy and Research.* International Food Policy Research Institute. Washington D.C, USA.
Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, 66, 695–706.

Kivlin, J.E., & Fliegel, F.C. (1967). Differential perceptions of innovations and rate of adoption. *Rural Sociology*, 32(1), 78-91.

Kumar, N., & Quisumbing, A. R. (2011). Access, adoption, and diffusion: understanding the long-term impacts of improved vegetable and fish technologies in Bangladesh. *Journal of Development Effectiveness*, *3*(2), 193-219.

Langyintuo, A. S., Diallo, W. M., MacRobert, A. O., Dixon, J., & Banziger, M. (2008). *An Analysis of the Bottlenecks affecting the production and deployment of maize seed in eastern and southern Africa*. CIMMYT.

Luan, Y., Cui, X., & Ferrat, M. (2013). Historical Trends of Food Self-Sufficiency in Africa. *Food Security*, 5(3), 397- 405.

Maasoumi, E., & Xu, T. (2015). Weights and substitution degree in multidimensional well-being in China. *Journal of Economic Studies*, 42(1), 4–19.

Malapit, H.J.L., & Quisumbing, A. R. (2015). What dimensions of women's empowerment in
agriculture matter for nutrition in Ghana? *Food Policy, 52*, 54–63.

Mayoux, L. (2006). 'Sustainable Micro-Finance for Women's Empowerment', A Report of the International Mutual Learning Workshop, September 4–8, Chennai, India.

Mazonde, I. N. (1993). Food policy and agriculture in Botswana. *Food policy and agriculture in Southern Africa. Harare: SAPES Books*.

Meijer, S. S., Catacutan, D., Ajayi, O. C., Sileshi, G. W., & Nieuwenhuis, M. (2015). The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa. *International Journal of Agricultural Sustainability*, *13*(1), 40-54.

Mendola, M. (2003). Agricultural technology and poverty reduction: A micro-level analysis of causal effects. *Centro Studi Luca D'Agliano Development Studies Working Paper*, (179), November, University of Milan-Bicocca, Italy.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy, 32*(3), 372–393.

Morrison, A., Raju, D., and Sinha, N. (2007). Gender equality, poverty and economic growth. The WB Policy Research Working Paper 4349.

Muzari, W., Gatsi, W., & Muvhunzi,S.(2012). The Impacts of Technology Adoption on Smallholder Agricultural Productivity in Sub-Saharan Africa: A Review, *Journal of Sustainable Development,* 5(8), 69-77.

Mwaniki, A. (2006). Achieving food security in Africa: Challenges and issues. *UN Office of the Special Advisor on Africa (OSAA)*.

Njuki, J., Waithanji, E., Sakwa, B., Kariuki, J., Mukewa, E., & Ngige, J. (2014). A qualitative assessment of gender and irrigation technology in Kenya and Tanzania. *Gender, Technology and Development*, *18*(3), 303-340.

Norton, G.W., Alwang,J., & Masters, W.E. (2006). *Economics of Agricultural Development: World Food Systems and Resource Use*. New York: Routledge.

Ogundari, K., & Bolarinwa, O. D. (2018). Does Adoption of Agricultural Innovations Impact Farm Production and Household Welfare in Sub-Saharan Africa? A Meta-Analysis. *Australian Journal of Agricultural and Resource Economics*, 59, 1–20.

Pressman, S., & Summerfield, G. (2000). The economic contributions of Amartya Sen. *Review of Political Economy, 12*, 89–113.

Quisumbing, A. R. (ed.) (2003). *Household Decisions, Gender, and Development: A Synthesis of Recent Research*. Washington, DC: IFPRI.

Quisumbing, A.R., **&** Maluccio, J. A. (2000). *Intrahousehold Allocation and Gender Relations: New Empirical Evidence from Four Developing Countries*. Washington, DC: IFPRI.

Quisumbing, A. R., & Maluccio, J.A. (2003). Resources at Marriage and Intrahousehold Allocation: Evidence from Bangladesh, Ethiopia, Indonesia, and South Africa. *Oxford Bulletin of Economics and Statistics,* 65 (3), 283–327.

Quisumbing, A.R., & Hallman, K. (2003). Marriage in Transition: Evidence on Age, Education, and Assets from Six Developing Countries. *Policy Research Division Working Paper 183. Population Council*.

Rahm, M. R., & Huffman, W.E. (1984). The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. *American Journal of Agricultural Economics*, 66 (4), 405–413.

Ravallion, M. (1996). Issues in Measuring and Modelling Poverty. *Economic Journal,* 106, 1328–1343.

Rawls, J. (1971). *A Theory of Justice*. Cambridge, MA: Harvard University Press

Rogers, E. M. (1962). *Diffusion of innovations, 3rd ed.* New York: Free Press.

Sahu, S. K., & Das, S. (2016). Impact of agricultural related technology adoption on poverty: A study of select households in Rural India. In *Technology* (pp. 141-156). Springer, Singapore.

Sanchez, P. A., Denning, G. L., & Nziguheba, G. (2009). The African green revolution moves forward. *Food Security*, *1*(1), 37-44.

Sen, A. (1976). Poverty. An Ordinal Approach to Measurement. *Econometrica*, 44, 219–231.

Sen, A. (1979). Personal Utilities and Public Judgments: Or what's wrong with Welfare Economics. *The Economic Journal*, 89, 537–558.

Sen, A. (1985). *Commodities and Capabilities.* Amsterdam: North-Holland.

Sen, A. (1987). *The Standard of Living*. Cambridge: Cambridge University Press.

Sen, A. (1992) *Inequality Re-examined.* Oxford: Clarendon Press

Sen, A. (1995). The Political Economy of Targeting, in D. van der Walle and K. Nead (eds), *Public Spending and the Poor. Theory and Evidence.* Baltimore: Johns Hopkins University Press.

Sen, A. (1996) Freedom, Capabilities, Public Action: a response, eds. Balestrina, A., Carter, I. pp. 107 – 125.

Sen, A. (1999) *Development as freedom,* 1st edition. New York: Knopf Press

Sharaunga, S., Mudhara, M., & Bogale, A. (2015, May). The impact of ‘Women's Empowerment in Agriculture ‘on household vulnerability to food insecurity in the KwaZulu-Natal Province. In *Forum for Development Studies* ,42(2), 195-223).

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272-284.

Skoufias, E. (2005). *PROGRESA and Its Impacts on the Welfare of Rural Households in Mexico. Research Report 139.* Washington, DC: IFPRI.

Smith, L. C., Ramakrishnan, U., Ndiaye, A., Haddad, L., & Martorell, R. (2003). The importance of women's status for child nutrition in developing countries: International Food Policy Research Institute (IFPRI) research report abstract 131. *Food and Nutrition Bulletin*, *24*(3), 287-288.

Sraboni, E., Malapit, H. J., Quisumbing, A. R., & Ahmed, A. U. (2014). Women’s empowerment in agriculture: What role for food security in Bangladesh? *World Development*, 61, 11–52.

Srabonia, E., & Quisumbing, A.R. (2018). Women’s empowerment in agriculture and dietary quality across the life course: Evidence from Bangladesh. *Food Policy, 81, 21–36.*

Stewart, F. (1985). *Planning to Meet Basic Needs*. London: Palgrave MacMillan

Streeten, P. (1981). *First Things First: Meeting Basic Human Needs in Developing Countries*. New York: Oxford University Press.

Thorbecke, E. (2008). Multidimensional Poverty: Conceptual and Measurement Issues, in N. Kakwani and J. Silber (eds), *The Many Dimensions of Poverty*. New York: Palgrave, pp. 3–19.

Tigabu, D. G., & Gebeyehu, M. F. (2018). Agricultural Extension Service and Technology Adoption for Food and Nutrition Security: Evidence from Ethiopia. *Forum for Agricultural Research in Africa (FARA) Research Report*, 3(4), 30.

Townsend, P. (1979). *Poverty in the United Kingdom: A Survey of Household Resources and Standards of Living*. London: Peregrine Books.

United Nations. Department of Public Information. (2009). *Millennium Development Goals Report 2009 (Includes the 2009 Progress Chart)*. United Nations Publications.

UN Economic and Social Council (ECOSOC) (2007). *Strengthening Efforts to Eradicate Poverty and Hunger, Including through the Global Partnership for Development. Report of the Secretary General*. New York: ECOSOC.

UN Economic and Social Council (ECOSOC) (2011). The empowerment of rural women and their role in poverty and hunger eradication, development and current challenges. Fifty-sixth session of the Commission on the Status of Women, 27 February-9 March 2012, New York.

United Nations Children’s Fund (2011). *Gender Influences on Child Survival, Health and Nutrition: A Narrative Review*. Available at: https://www. unicef.org/gender/files/Gender_Influences_on_Child_Survival_a_Narrative_review.

United Nations Development Program (UNDP) (2010). *Millennium Development Goals Report*. United Nations, New York, 2010.

Uthman, O. A., & Aremu, O. (2008) Malnutrition among women in sub-Saharan Africa: rural-urban disparity in Rural Remote Health, April-June; 8(2), 931. Available at: http://www.rrh.org.au/publishedarticles/article_print_931.pdf.

Verhart, N., Van Den Wijngaart, A., Dhamankar, M., & Danielsen, K. (2016). Bringing agriculture and nutrition together using a gender lens2. *Amsterdam, The Netherlands: SNV Netherlands Development Organisation (SNV) and the Royal Tropical Institute (KIT)*.

Von Braun, J., Teklu, T., & Webb, P. (1999). *Famine in Africa: Causes, responses, and prevention*. International Food Policy Research Institute.

World Bank (2008). *World development report 2008*: *agriculture for development.* Washington, DC: The World Bank.

Weymark, J. A. (2006). The normative approach to the measurement of multidimensional inequality. *Inequality and economic integration*, 303-328.

Wiggins, S. (2009). Can the smallholder model deliver poverty reduction and food security for a rapidly growing population in Africa? Future Agricultures Consortium (FAC), Working Paper No. 08, July 2009.

World Bank/IFAD/FAO (International Fund for Agricultural Development/Food and Agriculture Organization for the United Nations) (2009) Gender in agriculture sourcebook. World Bank, Washington, DC. http://siteresources.worldbank.org/INTGENAGRLIVSOUBOOK/Resources/CompleteBook.pdf.

World Food Programme (WFP). (2009a). *WFP Gender Policy and Strategy: Promoting Gender Equality and the Empowerment of Women in Addressing Food and Nutrition Challenges*. Rome: WFP.

Wu, H., Ding, S., Pandey, S., & Tao, D. (2010). Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching analysis in rural China. *Asian Economic Journal*, *24*(2), 141-160.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2014). Agricultural Technology Adoption and Child Nutrition: Improved Maize Varieties in Rural Ethiopia. Selected Paper prepared for presentation at the Agricultural and Applied Economics Association’s 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2015). Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics*, *46*(4), 515-526.

Collection of Paper in The Dissertation

Paper 1

A Meta-Analysis of the Impact of Improved Agricultural Technology Adoption on Welfare in Africa

Tsegaye Mulugeta and Almas Heshmati

Paper 2

Impact of Improved Agricultural Technology Adoption on Multidimensional Poverty in Rural Ethiopia

Tsegaye Mulugeta

Paper 3

Do Improved Agricultural Technologies Affect Household Food Security and Child Nutrition? The Case of Rural Ethiopia

Tsegaye Mulugeta

Paper 4

Agricultural Technologies and Women's Empowerment in Rural Ethiopia: Do Improved Agricultural Technologies Matter?

Tsegaye Mulugeta

Paper 1: A Meta-Analysis of the Impact of Improved Agricultural Technology Adoption on Welfare in Africa

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Abstract

A large body of research has documented the impact of adopting improved agricultural technologies on the productivity of staple crops and the welfare of smallholder agriculture farmers. However, the estimated effects of technology adoption differ among the studies. This paper presents a meta-analysis of empirical estimates using a sample of 52 empirical studies that investigated the impact of adopting improved agricultural technologies in Africa. A meta-analysis provides a family of statistical techniques for evaluating combined results of studies that are similar. We examine evidence of the impact of adopted agricultural technologies on three key sets of outcomes: output or expenditure, food security, and poverty. We also conduct tests for publication bias to see if researchers tend to report results in similar or different ways for the same outcome variable. Our findings shed light on the ways of identifying potential factors explaining the differences in the effects of estimated technology adoption. Our results also show that differences in the reported impact of technologies can be explained by factors like data type, model specification, whether theories are used or not, sample size, region of the study, and journal type. We observe no publication bias in the studies reviewed for the first and third models but there is some evidence of publication bias in the second model.

Keywords: Technology adoption; meta-analysis; agriculture; food security; poverty; Africa
JEL Classification Codes: C13; D13; D24; I30; N77; O14; Q16

1. Introduction

Adopting improved technologies for staple crop production is an important way of increasing the productivity of smallholder agriculture in Africa as this fosters economic growth and improved well-being of millions of poor households. However, as various studies indicate, basic descriptive data on the technologies used by farmers is rarely available. In contrast to many other parts of the world, many African governments do not collect or explore/report such data in a relevant form and in the required time. Without basic and descriptive information about who is adopting improved agricultural technologies and who is not, it is difficult to formulate effective policies aimed at increasing agricultural productivity (Doss, 2003).

Studies that focus on agriculture and welfare issues show that adopting improved agricultural technologies reduces poverty and food insecurity and increases farm household incomes and overall social welfare (Adekambi et al., 2009; Asfaw et al., 2010; Ferede et al., 2003; Hundie and Admassie, 2016; Kassie et al., 2010; Mendola, 2003, 2007; Mulugeta and Hundie, 2012; Shiferaw et al., 2013; Asfaw et al., 2012; Tesfaye et al., 2016; Wu et al., 2010). Many studies have also replicated, extended, and explored the impact of adopting agricultural technologies in different parts of the globe. There are large variations in the magnitude of the impact across studies which lead to questioning whether there is unambiguous evidence in the existing empirical literature on the link between technology adoption and welfare. Given the impact studies in the agriculture sector which have been done independently by different authors at various times and in various locations using different designs, methods, and datasets, it is very likely that they capture considerable heterogeneity and mixed effects in their impact evaluations. A traditional meta-analysis accumulates as broad a pool of cases as is possible from which inferences are made under the assumption that a sufficient population of cases will balance out individual methodological flaws (Slavin, 1995). It is also argued that the magnitude of the impact depends on the nature of the technology (for example, improved seeds, livestock technology, and improved practices), data type, methods of estimation, and the like.

A meta-analysis is a powerful methodology that collates research findings from previous studies and distils them for broader conclusions. It is, therefore, termed an ‘analysis of analyses.’ A meta-analysis can be helpful for policymakers who may be confronted by a mountain of conflicting conclusions (Alston et al., 2000). According to Stanley and Jarrell (1989), discuss any meta-analysis is the statistical analysis of statistical analyses in its very nature – it focus on the application of statistical methods to analyze, measure, and verify the varied statistical results from the empirical study of a particular phenomenon. Meta-analyses have become quite common in the fields of psychology and education. Although a meta-analysis does not supplant the expert judgments of specialists in the field, it does furnish a strategy to minimize the need for more subjective judgments while selecting studies for study, how to weigh the chosen studies, and when to dismiss apparently aberrant findings. A meta-regression analysis is a helpful framework for integrating, cumulating, and explaining disparate empirical economic literature.

The meta-analytical framework consists of a set of statistical and econometric methods which allow synthesizing outcomes from empirical studies carried out on a particular research question; it also helps in investigating their heterogeneity and mixed effects (Glass, 1976; Gorg and Strobl, 2001; Stanley, 2001; Stanley and Jarrell, 1989). It is a statistical procedure that integrates and up-scales numerous spatially and temporally distributed combinable micro-level studies to distil logical macro-level policy inferences. The inferences drawn based on a meta-analysis are often more objective and authentic (Joshi et al., 2005). The methodology also allows a combination of all relevant literature in a particular research area using statistical methods for evaluating, synthesizing, and testing existing evidence (Card and Krueger, 1995). A meta-analysis makes it possible to combine and contrast different studies for identifying patterns in existing findings and other relevant relationships which can only be observed in the context of multiple studies. By statistically combining the empirical results of existing studies, the 'power' of the analysis increases and hence the precision of the estimates also improves.

Some studies also state that a proper meta-analysis goes beyond a literature review in two ways. First, a meta-analysis includes all the studies that meet the review criteria and is thus comprehensive and forms a pool. It provides a basis for understanding why the impact differs among studies, over time, and among types of interventions. Second, with a large sample, a meta-analysis can make use of statistical techniques for summarizing and reviewing quantitative research to overcome limits of size or scope in individual studies and obtain more reliable information about the impact of a treatment. Because of these advantages a meta-analysis has become increasingly popular in recent decades. The methodology has been applied with increasing frequency, especially with randomized controlled trials in health, medicine, and psychology where randomized controlled trials are the research norm (WB, 2011).

The basic meta-analytical metric, namely the effect size, indicates the magnitude and the direction of the relationship between two variables. However, an issue of the non-equivalence of the effect size may arise here (Becker and Wu, 2007; Gorg and Strobl, 2001). The differences in effect size are a result of the fact that a variable is measured in different units in different studies and there are also disparities in the empirical specifications of the relationship. For instance, output is measured as total production, aggregate income, and percentage growth of annual income in most adoption literature. The question as to why the magnitude of regression coefficients differs across studies, however, remains unanswered. Despite this wide array of applied work in various studies, the extent to which empirical measures of the impact of agricultural technologies are sensitive to the choice of methodology remains a matter of controversy. Thus, an important task ahead in this field of inquiry is a more systematic effort to evaluate the performance of various impact evaluation estimators. This study is an attempt to narrow this gap and shed light on this issue by performing a meta-analysis of literature on the welfare impact of improved agricultural technology adoption in Africa.

We did a meta-analysis of a sample of 52 improved technology adoption studies focusing on the agriculture sector in Africa. To the best of our knowledge, this represents the first meta-analysis of the welfare impact of improved agricultural technology adoption in Africa. This paper contributes to existing research as it conducts a meta-analysis to test if the estimates obtained from the various studies vary as a result of differences in their contextual and methodological characteristics. We also conducted a publication bias test to examine if researchers were reporting positive and statistically significant values. Given the findings from these systematic reviews, it is worthwhile to examine if an empirical synthesis would lead to any new conclusions regarding the impact of improved technology adoption in African agriculture.

The rest of the paper is structured as follows. Section 2 presents the application of a meta-analysis in economics. Section 3 discusses the material and methods used; it specifically presents the key elements of the sample studies and discusses the data and variables. Section 4 discusses the meta-regression analysis, while Section 5 gives the regression results. Section 6 assesses the possible presence of a reporting bias by giving the publication bias tests conducted. Section 7 gives the main research findings of the study.

2. A Review of Meta-Analysis in Economics

A meta-analysis is quite popular in medical, educational, pharmaceutical, and marketing research (Thiam et al., 2001). As Stanley (2001) argues, a meta-analysis has been successfully employed in hundreds of applications throughout the social and medical sciences and in some limited form also in economics research. However, a review of literature shows that it has also been extended to a wide range of areas in economic research other than the impact of improved agricultural technologies. The methodology's application has been further extended to some more areas in recent times.

However, Gorg and Strobl (2001, p. F726) argue that, "while meta-analysis has been frequently applied in educational, psychological and medical research, its application in economics has been limited to a relatively small number of studies." They explain the possible reasons for this as most of the time the nature of the data used in economic research is non-experimental while data in the fields of education, psychology, and medicine is mainly experimental in nature. Stanley and Jarrell (1989) further argue that the problem of dependence on observations is likely to be no more important for meta-analyses than for primary econometric studies as these are not the result of controlled experiments either.

The first studies on meta-analysis in economics and specifically in the farm sector include the works of Thaim et al. (2001) who evaluated 34 farm studies in developing countries. Bravo-Ureta et al. (2007) conducted an extended analysis using 167 farm level studies in developed and developing countries. Later Lopez and Bravo-Ureta (2008) used the meta-analysis in the dairy sector. Their meta-analysis included 65 parametric and non-parametric published frontier studies. Ogundari (2009) examined Nigerian agriculture sector's efficiency performance from 1999 to 2008 by considering 64 published research articles. According to Bravo-Ureta et al. (2007), Ogundari (2009), and Thiam et al. (2001) meta-analyses on farm efficiency have particular flaws because these studies integrated the sample of developed and developing countries as a single population and set the average technical efficiency as a conjoint benchmark . A meta-analysis based on the overall technical efficiency performance of the farm sector, specifically in a single country case, gives a broader and meaningful picture. In addition, Bravo-Ureta and Pinheiro (1993) and Ogundari and Brümmer (2011) used a meta-analysis to investigate how technical efficiency scores from a primary study of agriculture and food production differed across studies.

Pattanayak et al. (2003) used a meta-analysis to examine agricultural technology use and analyzed 32 studies on the adoption of agro-forestry practices. Their study concluded that, factors considered in their study such as credit, savings, prices, market constraints and plot characteristics were found being important determinants of adoption behavior that are not well considered in previous studies. Similarly, Alston et al. (2000) conducted a meta-analysis of returns to agricultural R&D. They found that the characteristics of the analyst, research, and research evaluation all had important implications for the results. Rose and Stanley (2005) investigated the effects of common currencies on international trade and their results imply that if countries form a common currency, it has the potential of increasing bilateral trade by between 30 and 90 percentage points. Iwasaki and Tokunaga (2016) did a meta-analysis of technology transfers and foreign direct investment (FDI) spillovers in transition economies. Their meta-regression analysis showed that previous studies did not provide empirical evidence of a non-zero productivity spillover effect in the studied countries.

More recently, some economists have used the meta-analysis technique but there appears to be no application of this methodology in an analysis of the impact of improved technology adoption on staple crop agricultural production in Africa. Some of the studies are related to agriculture but are different from the focus area of our study. These include the impact of genetically modified (GM) crops (Klumper and Qaim, 2014); farm-level cost and benefit analysis of GM crops (Finger et al., 2011); economic and agronomic impact of commercialized genetically modified crops (Areal et al., 2013); impact of agricultural subsidies on farm technological efficiency (Minviel and Latruffe, 2014); impact of microfinance interventions (Awaworyi, 2014); an efficiency and productivity analysis of Pakistan's farm sector (Fatima and Yasmin, 2016); assessing the returns to water harvesting (Bouma et al., 2016); willingness to pay for reducing pesticide risk exposure (Florax et al., 2005); and nutrient management in African sorghum cropping systems and an assessment of yields and profitability (Tonitto and Ricker-Gilbert, 2016).[3]

Literature on meta-analyses applied to the non-agriculture field but relevant to our study is vast. Applications in diverse areas include the effects of immigration on wages (Longhi et al., 2005); income and calorie intake (Ogundari and Abdulai, 2013); income inequality and economic growth (de Dominicis et al., 2008); the impact of technical barriers to trade (Li and Beghin, 2012); effect of aid on economic growth (Mekasha and Tarp, 2013); energy consumption and economic growth (Chen et al., 2012); effect of currency unions on trade (Havránek, 2010); price and income elasticity of demand for meat (Gallet, 2010a, 2010b); price and income elasticity of demand for alcohol (Gallet, 2007); income elasticity of

[3] See Stanley (2001, pp.132-134) for more applications of meta-analysis in economics.

demand for cigarettes (Gallet and List, 2003); assessing the impact of interventions in fisheries' co-management in developing countries (Evans et al., 2011); exchange rate volatility and trade (Josheski and Lazarov, 2012); and debt and economic growth (Moore and Thomas, 2010).

3. Material and Methods

3.1 Literature Search

A meta-analysis is a statistical procedure that collates research findings from previous studies and distils them for a broader analysis and conclusions. As such it can be a major source of concise up-to-date information. It is a helpful framework for integrating and explaining disparate empirical economic literature. The overall conclusions of a meta-analysis, however, depend heavily on the quality of the meta-analytical process and an appropriate evaluation of the quality of the meta-analysis which can be challenging. To meet the required conditions, we performed extensive searches of adoption literature datasets. To begin with, we used a set of combined keywords search (meta-analysis, agriculture, staple crops, technology adoption, productivity, welfare, and Africa) in specific and important economics literature databases such as the Web of Science, the Web of Knowledge (WoK), Research Papers in Economics (RePEc), JSTOR, Science Direct, Research in Agricultural and Applied Economics (AgEcons), Econlit, Econpapers, and Google Scholar.

3.2 Description of the Sample and Variables

Originally 98 technology adoption studies were selected and put in a list for a meta-analysis. To be included in our meta-analysis, a study had to be an empirical study which assessed the impact of agricultural technologies on any of the three welfare indicator outcome variables -- output or expenditure, food security, and poverty indices -- conducted in Africa (we use output and income interchangeably). Consequently, we excluded studies that were not empirical and/or used any other outcome variables.

Literature discusses common prevalence of non-equivalence of effect size (Becker and Wu, 2007; Gorg and Strobl, 2001). The differences in effect size are a result of the fact that a variable is measured in different units. Many of the studies we used did not report a measure of mean values for output or expenditure, as well as average consumption and mean poverty levels we needed to construct a common scale. In the primary studies if the reported effect size was not comparable or if the results were in different measurements or scales, especially when those studies used variables with different scales and when such variables could not be transformed to a common scale the result was not comparable. Thus, we constructed a value in elasticity of interest form for the results reported in non-comparable form in the primary studies to find the desired and comparable effect size. Due to this and also to keep a large number of observations for the stability of our analysis we converted the value of output or expenditure, food security measures, and poverty indices obtained from the primary studies to a common scale (elasticity) form which is unit-free, is in uniform values or common scales and is easily comparable. However, the results reported in percentage (or elasticity) form in the primary studies are left as they appear. Table A1 in the Appendix shows the raw data obtained from the original studies (to make the table manageable all variables are not reported); the effect size was constructed from these reported results using the technique mentioned earlier.

We excluded 46 studies that did not meet our criteria and thus our sample consists of 52 studies covering different regions of the African continent (see Appendix Table A1 and A2 for a listing of the studies). These studies were obtained after inspecting recent studies on the wider area of the impact of agricultural technology adoption in Africa. A majority of the papers included in our study are on adoption impacts in East Africa (Ethiopia, Kenya, Uganda, and Tanzania). The remaining papers are from West and South Africa. The relatively large sample size of 52 studies allowed us to include a large number of meta-independent variables and unlike other studies our study is not constrained by problems related to low degrees of freedom.

The independent variables called ‘moderator variables’ by Stanley (2001) are those study characteristics that are thought to be consequential. There is some latitude for identifying what these key characteristics should be based on like the nature of the study, sample size and quality, methods used, and relevant theories. At a minimum, a meta-analyst will wish to code dummy variables for the use of different datasets and econometric modeling choices. However, because the number of studies is limited, and most studies entail a unique combination of theory, estimation methods, explanatory variables, data, time periods, and other research related choices, not every uncommon study characteristic can be coded and analyzed. Variations due to minor modeling choices may be treated as part of the random study-to-study background. We selected and defined several potential moderator variables which primarily represent differences in econometric specifications in our technology adoption studies.

These moderator variables include accounting for the nature of the data for which we used a dummy variable, whether the data types are cross-section or panel data (DATA). In addition, we also used a regional dummy: East Africa, North Africa, Southeast Africa, Central Africa, and West Africa (REGION=1 if the study was in East Africa, 0 if it was elsewhere). We also used dummy variables to account for differences in estimation techniques, PSM (propensity score matching), ESR (endogenous switching regression), and OLS (ordinary least squares), etc. (MODEL=1 if the study used the PSM/ESR method, 0 otherwise) and if the study used any theory (THEORY=1). There were also dummy variables for whether the type of technology was improved seeds (TECHNO=1, 0 otherwise). Further, we calculated a set of dummy variables to account for different journal types (JOURNAL=1 if it was published in a peer-reviewed journal, 0 for studies published elsewhere). Other variables include year of publication (YEAR) and sample size (SAMPLE). The full list of dependent and independent variables used in the meta-regression is given in Table 1.

Table 1: Definitions of dependent and independent variables used in the meta-analysis

Variable	Definition
Dependent:	
Total income or expenditure (Y/E)	Total amount of income (output) or expenditure reported in the primary studies
Food security (FS)	Food security levels reported in the primary studies
Poverty (PO)	Poverty index (in %) reported in the primary studies
Independent:	
YEAR	Year of publication
DATA	1 if the data used was cross-sectional, 0 otherwise
REGION	1 if the study was in East Africa, 0 elsewhere
THEORY	1 if the study used a theory, 0 otherwise
MODEL	1 if the study used PSM/ESR methods, 0 otherwise
TECHNO	1 if the technology was improved seeds, 0 otherwise
SAMPLE	The sample size used in the selected studies
JOURNAL	1 if the study was published in a peer-reviewed journal, 0 otherwise

Source: Authors' definitions (2018).

Figure 1 shows the distribution of the outcome of raw data and some of the moderator variables from the primary studies plotted against regions and the types of technology adopted. The observed variations in the distribution of these outcome variables (Figure 1a) show that there were clear regional differences in the impact of the various agricultural technologies in different parts of the continent (additional figures are also given in the Appendix).

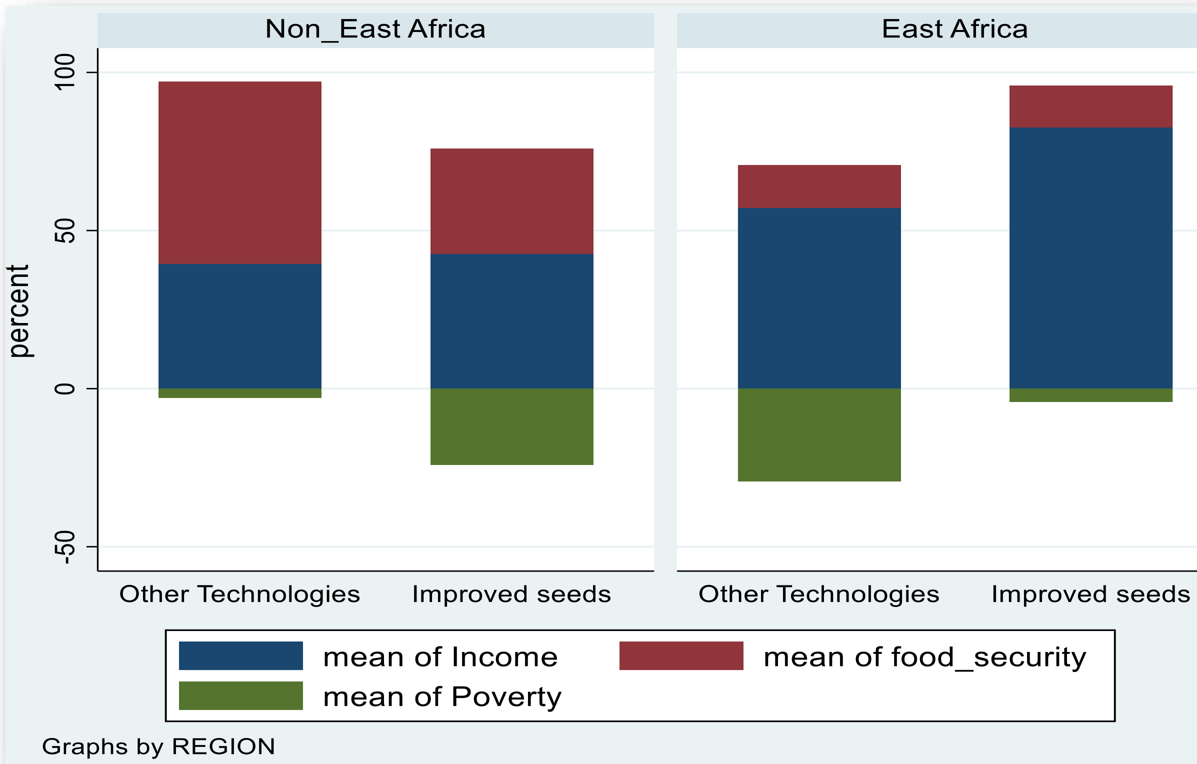


Figure 1a. Distribution of Outcomes by regions and types of technology adopted

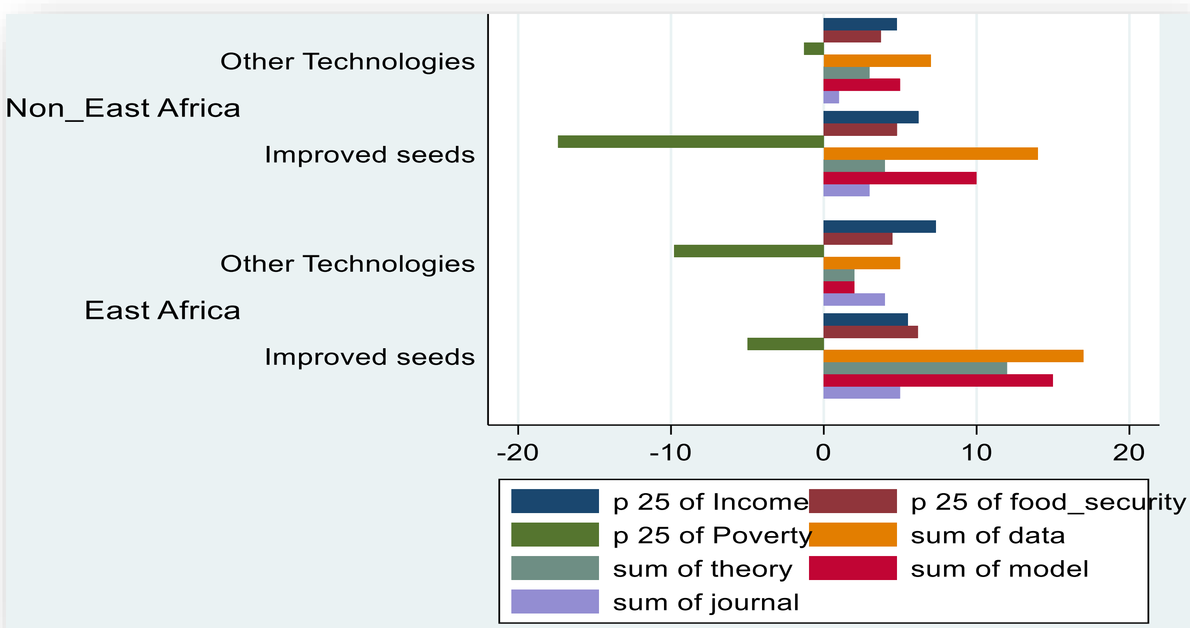


Figure 1b. Distribution of the 25 percentile values of outcomes and total values of the four explanatory variables by regions and technology type

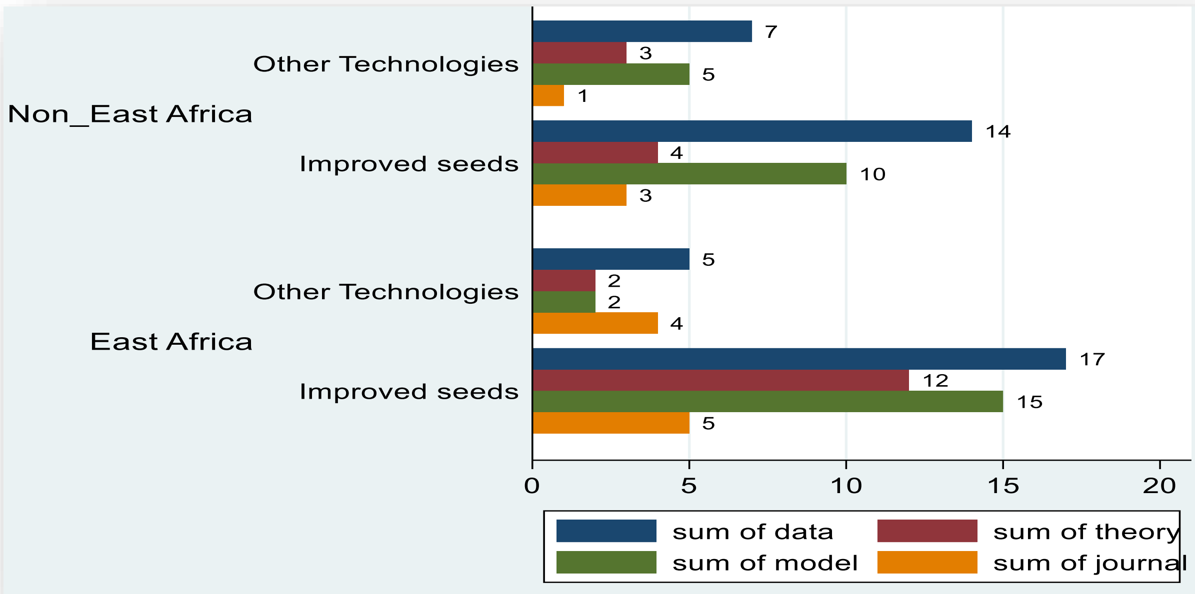


Figure 1c. Total value distribution of the explanatory variables by regions and technology type

4. The Meta-Regression Analysis

To explore and assess the variations in the results across the sample studies concerning the welfare impact of improved agriculture technology adoption in the African context we did a meta-regression analysis suggested by Stanley and Jarrell (1989, 1990); Card and Krueger (1995); Stanley (2001); and Gorg and Strobl (2001). As stated earlier, our study used the three outcome variables to capture the reported impact of adopting improved agricultural technologies on welfare in Africa from the primary studies. In doing so, we estimated an equation for integrating the empirical results across different studies:

$$(1) \qquad Y_j = \beta_0 + \sum_{k=1}^{K} \beta_k Z_{jk} + e_j \qquad j = 1,\ 2,\ \ldots, N$$

where Y_j is the reported impact estimate of the outcome in study j from a total of N studies and Z_{jk} is a vector of meta-independent variables which measure relevant characteristics of an empirical study that might explain effect variations in $Y_j\,s$ across studies in the meta sample, β_k is a vector of unknown parameters to be estimated, and e_j represents the unexplained variations in the dependent variable or the random error term. The estimated effect β_k indicates the effect of specific sample characteristics on the outcome variable.

5. Estimation Results

Model 1: Output or Expenditure

We estimated the linear regression models separately for the three outcome variables (output or expenditure, food security, and poverty indices) all expressed in percentage points. Table 2 presents the OLS' estimates with robust standard errors of the meta-regression analysis for the three outcome variables. For a comparison a weighted least square (WLS) was estimated, but the results are a bit similar to robust OLS estimation results and these are not reported here. The OLS results show different factors influencing impact heterogeneity across the sample studies.

The dependent variable for the first model estimated (Column 1,) is output or expenditure from the sample studies. The intercept term, or β_0 from Equation (1) is an estimate of technology adoption on output or expenditure given zero effects from the slope determinants. The estimated intercept is statistically insignificant interpreted as not being different than zero. The parameter estimates of the publication year of the study, while negative, are not statistically significant. This suggests that reported percentage points of output or expenditure decreased over time, but this reduction is not statistically significant across periods. The results show that recent studies reported lower impacts of agricultural technology adoption on welfare represented by output or expenditure and measured in percentage points (elasticity or percentage changes in output effect with respect to a change in the time period).

Studies based on cross-sectional data exhibit significantly lower percentage points of output or expenditure estimates than those using panel data or time series. In other words, the effect of improved agriculture technology adoption appears to be lower in cross-sectional studies. Models relying on panel data are likely to yield more accurate efficiency estimates given that there are repeated observations of each unit (Baltagi, 2015) and one can account for long run or dynamic effects of technology adoption. However, no *a-priori* expectations of the impact of data type (cross-sectional versus panel data) on the magnitude of percentage points of output or expenditure values are developed in our study. Other studies also state that this difference across data types may arise because of problems associated with unobserved time invariant heterogeneity effects. Specifically, if there are time-invariant effects across the individual units then the cross-sectional studies may produce biased and inconsistent estimates. Such time-invariant effects may, however, be eliminated by within-mean transformations or changes over time if panel data is used (Baltagi, 2015; Gorg and Strobl, 2001).

Our results confirm that studies that use East African countries in their analyses report higher output or expenditure values as compared to other regions of the African continent. This suggests that improved agricultural technology adoption in East Africa has a bigger effect on families' output or expenditure than those used elsewhere on the continent. Estimates of whether a primary study used any theory or not and the sample sizes of those studies do not significantly affect the output or expenditure elasticity estimates across the sample studies.

Table 2: Meta-regression analysis results: OLS with robust standard errors

Variables	Model 1	Model 2	Model 3
	Output/Expenditure	Food security	Poverty index
YEAR	-2.16	0.799***	-2.34**
	(1.51)	(0.12)	(1.08)
DATA	-143.90***	__	-13.18**
	(45.48)		(5.98)
REGION	59.63**	-8.995**	-8.72**
	(28.43)	(3.72)	(3.55)
THEORY	-13.18	9.665*	__
	(40.64)	(4.77)	
MODEL	84.65**	__	7.10*
	(38.56)		(3.70)
SAMPLE	0.002	-0.005**	-0.005**
	(0.011)	(0.001)	(0.002)
JOURNAL	-18.85	__	-10.79*
	(24.63)		(5.27)
CONSTANT	4436.86	-1587.48***	4737.44**
	(3018.79)	(246.87)	(2175.54)
No. of obs.	46	13	19
Adjusted R^2	0.214	0.613	0.466

Notes: Robust standard errors in parentheses below the coefficients. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Source: Authors' computations.

Our study also analyzed whether the statistical method used played a role in arriving at the results. Studies that used propensity score matching (PSM) or the endogenous switching regression (ESR) approach or both yielded significantly higher output or expenditure effect values than those that used OLS, logit, probit, or tobit estimation methods. This result is striking in that recent studies employ estimation techniques like the endogenous switching regression approach that take into account issues such as sample selection bias and heterogeneity of sample units while many of the earlier studies partly or totally failed to account for such aspects affecting the properties of the estimated effects.

Additionally, our study examined whether the type of publication mattered in the variations in technology adoption effects among the studies investigated. Keeping the other factors fixed, the regression coefficients for the variable journal reported in Table 2 show that studies published in peer-reviewed journals had lower estimated gains in output or expenditure as compared to studies published elsewhere, but this was not statistically significant. When only observations from studies that were published in peer-reviewed journals are included, the mean effect size is larger than when all observations are included. In this regard, one can suspect the presence of a bias in the publication of those studies, which implies that only studies that report substantial effects are more likely to be accepted for publication in a journal (Borenstein et al., 2009). Second, even if there is publication bias, our mean results will be estimated correctly (this issue is dealt with in greater detail in Section 6, under test of publication bias). In Section 6 when testing publication bias this meta-analysis also includes studies that were not published in peer-reviewed journals.

Model 2: Food security

For the second outcome variable of food security levels, Model 2 is estimated with only four of the most important independent variables due to fewer observations and also to not lose the degree of freedom. Thus, the small size of our sample prevents the inclusion of additional moderator variables. The results of the meta-regression using OLS are reported in Table 2, Column 2. The parameter estimate of the year of the study is positive and statistically significant. This implies that reported probabilities of being food secure (percentage gain of food security levels) increased significantly over time. This suggests that recent studies have reported higher gain of improved technology adoption as measured by food security.

The variable REGION indicates whether the study was based in East African countries or not. It allows us to test for the differences in the regional effects of technology adoption. The results show that studies that covered East African countries in their analyses reported lower food security gains as compared to studies elsewhere on the continent. Our findings also suggest that it actually matters whether a study uses a specific theory or not. Studies that used theories reported higher percentage gains of food security as compared to studies that were ad-hoc and built without a specific theory; this was also statistically significant. Another way of explaining this result is that primary studies that employed theory in their work reported a significant impact of improved agricultural technologies when the potential outcome variable was food security levels.

When it comes to sample size of the studies included in our analysis, our results show that studies with smaller sample sizes reported higher percentage gains of food security. This implies that reported probabilities of being food secure differed across studies with different sample sizes. A larger sample is expected to result in more stable and accurate technology adoption effects on food security, but our results went the other way.

Model 3: Poverty index

The OLS estimation results with robust standard errors for the third outcome variable (poverty index) are reported in Table 2 (Column 3) where the dependent variable is poverty indices from the sample studies.

An estimation of the model shows that the year of the study for the poverty index estimation was negative and statistically significant. This implies that the reported poverty indices decreased significantly over time and confirms that earlier studies reported higher reduction in poverty and hence a higher impact of agricultural technologies on welfare as measured by poverty indices. Our results also show that studies based on cross-sectional data had significantly lower poverty reduction in percentage points than those using panel or time series data. In other words, the impact of improved agriculture technology adoption was estimated to be lower in cross-sectional studies. Panel data captures the dynamic and accumulated learning by studying the effects of technology adoption.

Our results confirm that when it comes to regional effects of technology adoption, studies that used data from East African countries reported lower poverty reduction as compared to other regions. Our study also shows that studies using propensity score matching or endogenous switching regression approaches or both yielded higher poverty reduction than those that used other estimation techniques. This result is statistically significant at the 10 percent probability level. Studies that used a larger sample size reported lower reduction in poverty. Hence, our results indicate a negative and statistically significant link between poverty reduction and sample size as indicated in Column 3 of Table 2.

Lastly, our study examined whether the type of publication mattered for the technology adoption effect. In this case the regression coefficient for the variable journal publication of Model 3 indicates that studies published in peer-reviewed journals reported lower reduction in poverty as compared to similar studies published elsewhere; this was also statistically significant.

6. Test of Publication Bias

In research, academic journals have a tendency to publish papers with 'statistically significant' results and those which are consistent with expectations determined by the theory used (Begg and Berlin, 1988; De Long and Lang, 1992). In many studies, publication bias has been generally recognized as yet another threat to the relevance of applied economics. Concerning publication bias, De Long and Lang (1992, p. 1258) state, "... even a careful review of the existing published literature will not provide an accurate overview of the body of research in an area if the literature itself reflects selection bias." This may be especially true in cases in which the research concerns are a parameter that is predicted to have a certain sign using the conventional economic theory. In this case, insignificant or 'wrong-signed' results may be substantially under-reported in the published research.

According to Stanley (2008, p. 104), "econometric estimates can easily be overwhelmed by publication selection because there are so many plausible econometric models to choose from. Conventional literature reviews and econometric techniques are powerless to address publication bias." Nowadays the econometric methodology cannot reliably assess the empirical merit of any economic hypothesis. Issues of publication selection and its identification and circumvention are crucial for genuine empirical economics.

More recently, researchers have also investigated the issue of publication bias. These include Abreu et al. (2005), Ashenfelter et al. (1999), Card and Krueger (1995), Doucouliagos (2005), Doucouliagos et al. (2005), Gorg and Strobl (2001), Nijkamp and Poot (2005), Rose and Stanley (2005), and Stanley (2001, 2005a, 2005b).

However, it should also be noted that publication bias need not arise from some deliberate motive to deceive. Authors may be less likely to submit statistically insignificant results because of the 'rational' expectation that they will have a lower probability of being accepted. Or referees and editors may disproportionately select significant results believing them to be more informative. In either case, insignificant empirical findings will be under-represented, and any unadjusted summary of research literature will be biased in favor of the investigated effects irrespective of the motivation of the researchers. Needless to say, a prior commitment to a given ideological or theoretical position can greatly compound the publication bias.

There are some common methods for testing publication bias. For example, Card and Krueger (1995) suggest two types of tests for publication bias. Unfortunately, we could not perform either of these tests or follow common methods for testing publication bias because a majority of our sample studies employed non-linear functional forms which make the tests inappropriate using specified methods as they do not provide information on sample means of income or expenditure, average food consumption, or poverty level adopters and non-adopters. Very few studies in our sample used a linear specification which does not allow us to run a meaningful regression on the sample.

Another alternative and common way of assessing possible publication bias in a meta-analysis is a funnel plot (see Figures 2-4) and a funnel asymmetry test (FAT)-MRA approach. The first method, a funnel plot, is a simple scatter plot of intervention effect estimates (effect size) from individual studies against some measure of each study's size or precision. A funnel plot is a graph that shows the relationship between effect size and a measure of precision such as a standard error or inverse of standard error of the effect size. Literature on meta-analysis states that funnel plots are more likely to be vulnerable to subjective interpretations (Stanley, 2005a) and consequently, alternative methods like FAT-MRA are used in combination with funnel plots to validate the existence of publication bias in the sampled primary studies.

Here we follow the second publication bias test method proposed by Card and Kruger (1995) of regressing the effect size estimate on its standard error (log of square root of sample size is used as a proxy in our case). Begg and Berlin (1988) also argue that sample sizes are usually not planned and instead depend mainly on the availability of data and computing powers. Thus, it may be reasonable to assume that the sample size is determined without any meaningful association with its underlying true random effect. This assumption then allows us to investigate a publication bias by analyzing whether there is indeed no meaningful relationship between sample size and our three outcome variables.

Concerning the empirical approaches of publication bias, Egger et al. (1997) proposed a method of FAT-MRA by regressing a measure of precision on the effect size of interest, which can be specified as:

(2) $$Effect_{ij} = \beta_0 + \beta_1 P_{ij} + \varepsilon_{ij}$$

where *Effect* is the measure of effect size of each study, *P is* the study's size or precision, β_0 and β_1 are estimated parameters, and ε_{ij} stands for the random error term.

Publication bias exists when the correlation between the study's effect size (*Effect*) and the study's size gives a statistically significant result. This suggests that a large proportion of the primary studies with significant effect size perhaps dominate the literature under review. In the absence of publication bias, the effect size of the primary studies is less likely to correlate significantly with the study's size.

The first test for the existence of publication bias is the funnel plots reported for all the three outcome variables (after proper construction and conversion to effect size, as stated in

Section 3.2) in Figures 2-4. Figure 2 shows the relationship between output (expenditure) and the log of the square root of the sample size (logsqsample) in the included studies. We would expect a positive relationship between output estimates and sample size but this does not appear to be the case for our data shown in the graph and it is not obvious from Figure 2 whether there is any relationship or not between the two, and thus the plot does not provide any evidence of association of the two variables. The same thing can be seen in Figure 4 where the relationship is not clear, but in Figure 3 there seems to be a weak relationship between food security and sample size; and thus, publication bias exists in the second model.

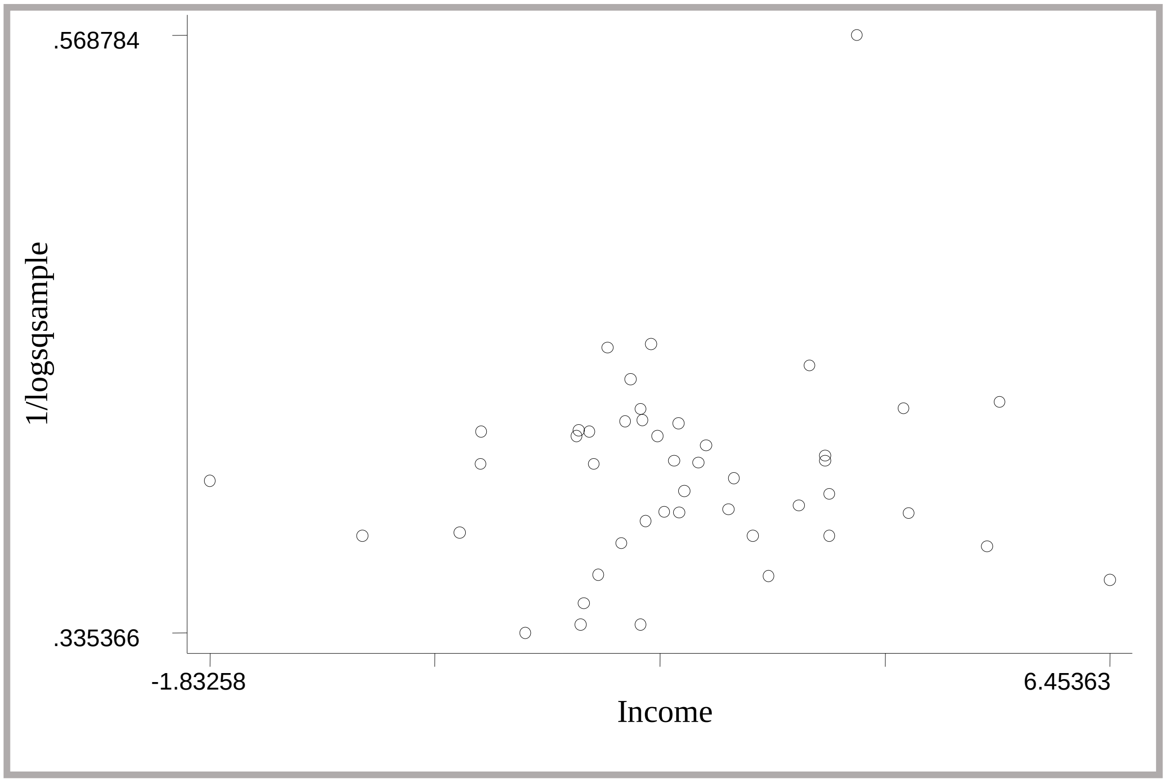


Figure 2: Funnel plot of Income against inverse of logsqsample
Source: Authors' computations.

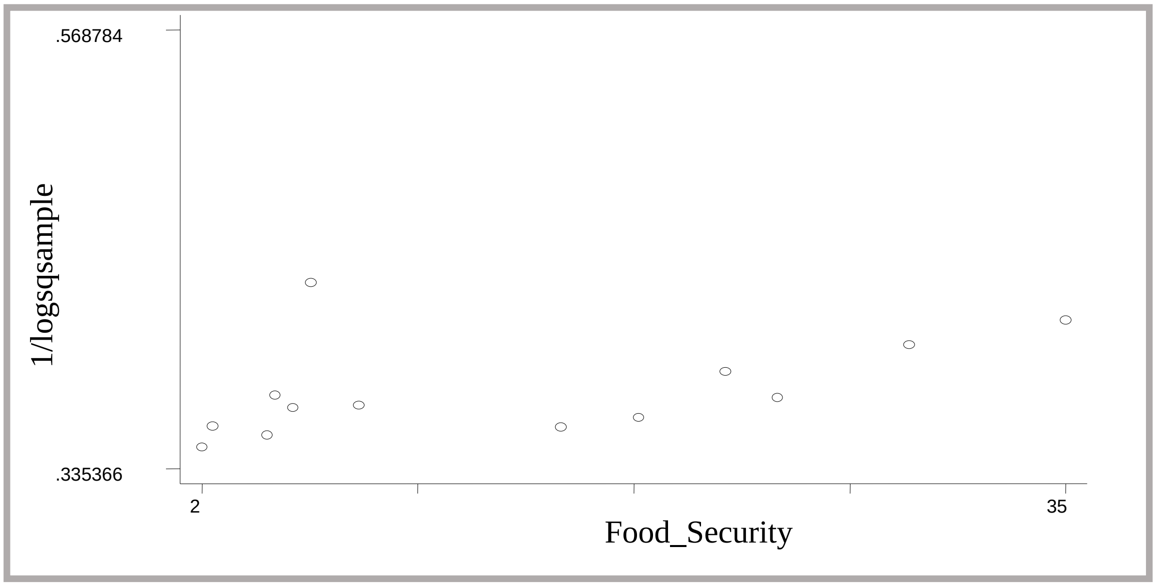


Figure 3: Funnel plot of food security against inverse of logsqsample
Source: Authors' computations.

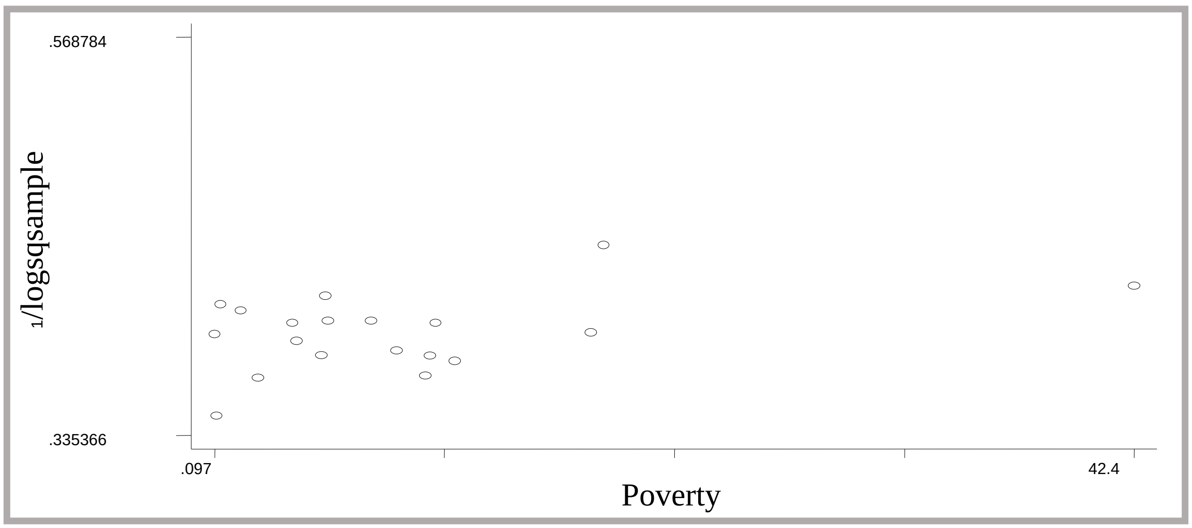


Figure 4: Funnel plot of poverty index against inverse of logsqsample
Source: Authors' computations.

Confirming the meta-regression-analysis' results, the funnel plot also shows that there is no publication bias in the first and third models of our sample studies, but a publication bias exists in the second model. The absence of a publication bias (in the two models), is perhaps due to the inclusion of more studies that were not published in peer-reviewed journals.

A visual inspection of the funnel plots can be subjective, so we also estimated the FAT-MRA as an empirical test to further investigate the existence of publication bias. The results are presented in Table 3.

Table 3: Estimated funnel asymmetry test (FAT)-MRA

	Output (Expenditure)	Food security	Poverty index
Sample size	-0.13(0.21)	-6.33*(3.23)	-5.22(3.00)
Constant	3.35**(1.35)	58.74**(23.16)	42.25*(19.16)
N	46	13	19

Note: Standard errors are in parenthesis; *, ** shows that estimates are significant at the 10% and 5% level respectively.

Source: Authors' computations.

The results in Table 3 show that the study's size or precision (sample size in our case) for the first and third outcomes is statistically insignificant supporting the funnel plot presented earlier and confirm that there is no publication bias in those models. In the second model, however, the results of the estimate of sample size are statistically significant providing evidence of the existence of a publication bias. This confirms the results of the funnel plots and thus shows that publication bias exists in the food security model.

7. Conclusion

A large body of literature has analyzed the impact of adopting improved and modern agricultural technologies on welfare. However, these studies have many variations and report different effects across different parts of the African continent. A meta-analysis is one of the best ways of shedding light on unexplained variations across studies. The basic objective of conducting a meta-analysis in this study was to understand the large variations in the results of selected studies. Through a meta-analysis of a large sample of studies, this paper identified important factors that influenced the welfare impact of agricultural technology adoption in Africa using three outcome variables.

For the first outcome variable (output/expenditure) the results showed that studies based on cross-sectional data had significantly lower percentage points of output or expenditure estimates than those using panel or time series data, and studies that used data from East African countries in their analyses reported higher output or expenditure values compared to studies in the other regions. We also found that studies using propensity score matching or endogenous switching regression approaches or both yielded significantly higher output or expenditure percentage values as compared to those employing other estimation methods.

For the second outcome variable (food security levels), the meta-analysis showed that the year of the study and studies that used theories in their original work reported relatively higher and positive percentage gains in food security as a result of improved technology adoption in the agriculture sector. It was also observed that studies that used East African countries in their analyses and studies with larger sample sizes reported lower food security.

Finally, for the third outcome variable (poverty index), the meta-analysis showed that all the significant variables -- year of the study, data type, sample size, journal type, and regions studied -- reported significantly lower poverty index reduction in percentage points while only the variable, model type, reported significantly higher poverty index reduction.

The meta-regression analysis also showed that there was no evidence of publication bias in the first and third models, but in the second model the test's results showed that publication bias existed. This absence of publication bias in the two models might be attributed to the fact that we also included studies that were not published in peer-reviewed journals along with studies reviewed in peer reviewed journals. Such studies reported lower reduction in poverty as compared to studies published elsewhere and the technology adoption effects were statistically significant. This can explain the absence of publication bias.

We observed some important implications of the meta-analysis which are not much studied in the agriculture sector and are quite rare in development economics. Based on the meta-analysis, our results highlight the important role of a study's attributes of factors that explain variations in the reported impact of agricultural technologies and improved practices on selected outcome variables in the African context identified in our investigation. Based on these results, our findings of the meta-analysis can be very useful for advancing such an approach in the agriculture sector; this will also motivate researchers in identifying study-specific attributes essential for modeling the impact of different agricultural technologies and modern practices in the sector. Our study can also be a starting point for evaluating the sensitivity of studies in terms of the choice of different methodologies, especially the type of model specifications (and /or functional forms), and estimation methods. In addition, we believe that our findings have improved our understanding of the various impacts of modern agricultural innovations and technology adoption which improve the application of appropriate and optional policy analyses in the agriculture sector.

References

Abreu, M., De Groot, H. L., & Florax, R. J. (2005). A meta-analysis of β-convergence: The legendary 2%. *Journal of Economic Surveys*, *19*(3), 389-420.

Adekambi, S. A., Diagne, A., Simtowe, F., & Biaou, G. (2009). The Impact of Agricultural Technology Adoption on Poverty: The Case of, NERICA Rice Varieties in Benin. Contributed paper prepared for presentation at the International Association of Agricultural Economists' conference, Beijing, China, August 16-22, 2009.

Alston, J. M., Marra, M. C., Pardey, P. G., & Wyatt, T. J. (2000). Research Returns Redux: A Meta-Analysis of the Returns to Agricultural R&D. *The Australian Journal of Agricultural and Resource Economics, 44(2),* 185-215.

Areal, F. J., Riesgo, L., & Rodriguez-Cerezo, E. (2013). Economic and agronomic impact of commercialized GM crops: a meta-analysis. *The Journal of Agricultural Science*, *151*(1), 7-33.

Asfaw, S., Shiferaw, B., & Simtowe, F. (2010). Does technology adoption promote commercialization? Evidence from chickpea technologies in Ethiopia. In *CSAE 2010 conference on Economic Development in Africa, University of Oxford, UK*.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295.

Ashenfelter, O., Harmon, C., & Oosterbeek, H. (1999). A review of estimates of the schooling/earnings relationship, with tests for publication bias. *Labour economics*, *6*(4), 453-470.

Awaworyi, S.K (2014). Impact of microfinance interventions: a meta-analysis. *Business and Economics*, *4*(1), 3-14.

Baltagi, B. H. (Ed.). (2015). *The Oxford handbook of panel data*. Oxford Handbooks.

Becker, B. J., & Wu, M. J. (2007). The synthesis of regression slopes in meta-analysis. *Statistical science*, *22*(3), 414-429.

Begg, C. B., & Berlin, J. A. (1988). Publication bias: a problem in interpreting medical data. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *151*(3), 419-445.

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to Meta-Analysis*. Chichester: John Wiley and Sons.

Bouma, J. A., Hegde, S. S., & Lasage, R. (2016). Assessing the returns to water harvesting: A meta-analysis. *Agricultural water management*, *163*, 100-109.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1993). Efficiency analysis of developing country agriculture: a review of the frontier function literature. *Agricultural and resource economics Review*, *22*(1), 88-101.

Bravo-Ureta, B. E., Solís, D., López, V. H. M., Maripani, J. F., Thiam, A., & Rivas, T. (2007). Technical efficiency in farming: a meta-regression analysis. *Journal of productivity Analysis*, *27*(1), 57-72.

Card, D., & Krueger, A. B. (1995). Time-series minimum-wage studies: A meta-analysis. *American Economic R*eview, 85(2), 238-243.

Chen, P. Y., Chen, S. T., & Chen, C. C. (2012). Energy consumption and economic growth—New evidence from meta-analysis. *Energy policy*, *44*, 245-255.

De Dominicis, L., Florax, R. J., & De Groot, H. L. (2008). A meta-analysis on the relationship between income inequality and economic growth. *Scottish Journal of Political Economy*, *55*(5), 654-682.

De Long, J. B., & Lang, K. (1992). Are all economic hypotheses false? *Journal of Political Economy*, *100*(6), 1257-1272.

Doss, C.R. (2003). Understanding Farm Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa. CIMMYT Economics Working Paper 03-07. Mexico, D.F.: CIMMYT.

Doucouliagos, C. H. (2005). Publication bias in the economic freedom and economic growth literature. *Journal of Economic Surveys*, *19*(3), 367-387.

Doucouliagos, H., Laroche, P., & Stanley, T. D. (2005). Publication bias in union-productivity research? *Relations Industrielles/Industrial Relations*, *60*(2), 320-347.

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal*, *315*(7109), 629-634.

Evans, L., Cherrett, N., & Pemsl, D. (2011). Assessing the impact of fisheries co-management interventions in developing countries: A meta-analysis. *Journal of environmental management*, *92*(8), 1938-1949.

Fatima, H., & Yasmin, B. (2016). Efficiency and Productivity Analysis of Pakistan's Farm Sector: A Meta-Analysis. *Pakistan Journal of Agricultural Research*, 29(3), 312-322.

Ferede, S., Teklewold, H., & Ayele, G. (2003). *Impact of technology on household food security in tef and wheat farming systems of Moretna-Jiru wereda*. Ethiopian Agricultural Research Organization, Research Report No.48.

Finger, R., El Benni, N., Kaphengst, T., Evans, C., Herbert, S., Lehmann, B., ... & Stupak, N. (2011). A meta-analysis on farm-level costs and benefits of GM crops. *Sustainability*, *3*(5), 743-762.

Florax, R. J., Travisi, C. M., & Nijkamp, P. (2005). A meta-analysis of the willingness to pay for reductions in pesticide risk exposure. *European Review of Agricultural Economics*, *32*(4), 441-467.

Gallet, C. A. (2007). The demand for alcohol: a meta-analysis of elasticities. *Australian Journal of Agricultural and Resource Economics*, *51*(2), 121-135.

Gallet, C. A. (2010). Meat meets meta: a quantitative review of the price elasticity of meat. *American Journal of Agricultural Economics*, *92*(1), 258-272.

Gallet, C. A. (2010b). The income elasticity of meat: a meta-analysis. *Australian Journal of Agricultural and Resource Economics*, *54*(4), 477-490.

Gallet, C. A., & List, J. A. (2003). Cigarette demand: a meta-analysis of elasticities. *Health economics*, *12*(10), 821-835.

Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. *Educational researcher*, *5*(10), 3-8.

Gorg, H., & Strobl, E. (2001). Multinational companies and productivity spillovers: A meta-analysis. *The economic journal*, *111*(475), F723-F740.

Havránek, T. (2010). Rose effect and the euro: is the magic gone? *Review of World Economics*, *146*(2), 241-261.

Hundie, B., & Admassie, A. (2016). "Potential Impacts of Yield-Increasing Crop Technologies on Productivity and Poverty in two Districts of Ethiopia", in F. Gatzweiler and J. von Braun (eds), *Technological and Institutional Innovations for Marginalized Smallholders in Agricultural Development.* Springer International Publishing (pp. 397-421).

Iwasaki, I., & Tokunaga, M. (2016). Technology transfer and spillovers from FDI in transition economies: A meta-analysis. *Journal of Comparative Economics*, *44*(4), 1086-1114.

Josheski, D., & Lazarov, D. (2012). Exchange rate volatility and trade: a meta-regression analysis. *GRP International Journal of Business and Economics*, 1(2), 24-49.

Joshi, P. K., Jha, A. K., Wani, S. P., Joshi, L., & Shiyani, R. L. (2005). Meta-analysis to assess impact of watershed programme and people's participation. Research Report

No. 8. International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru 502 324, Andhra Pradesh, India.

Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda. *Environment for Development Discussion Paper-Resources for the Future (RFF)*, (10-11).

Klümper, W., & Qaim, M. (2014). A meta-analysis of the impacts of genetically modified crops. *PloS one*, *9*(11).

Li, Y., & Beghin, J. C. (2012). A meta-analysis of estimates of the impact of technical barriers to trade. *Journal of Policy Modeling*, 34, 497–511.

Longhi, S., Nijkamp, P., & Poot, J. (2005). A meta-analytic assessment of the effect of immigration on wages. *Journal of economic surveys*, *19*(3), 451-477.

Lopez, M.V.H., & Bravo-Ureta, B.E. (2008). A study of dairy farm technical efficiency using meta-regression: An international perspective. *Chilean Journal of Agricultural Research*, 69, 214-223.

Mekasha, T. J., & Tarp, F. (2013). Aid and growth: What meta-analysis reveals. *The journal of development studies*, *49*(4), 564-583.

Mendola, M. (2003). Agricultural technology and poverty reduction: A micro-level analysis of causal effects. *Centro Studi Luca D'Agliano Development Studies Working Paper*, (179), November, University of Milan-Bicocca, Italy.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy, 32*(3), 372–393.

Minviel, J. J., & Latruffe, L. (2014). Meta-regression analysis of the impact of agricultural subsidies on farm technical efficiency. Paper prepared for presentation at the EAAE 2014 Congress Agri-Food and Rural Innovations for Healthier Societies. August 26-29, Slovenia.

Moore, W., & Thomas, C. (2010). A meta-analysis of the relationship between debt and growth. *International Journal of Development Issues*, 9(3), 214-225.

Mulugeta, T., & Hundie, B. (2012). Impacts of Adoption of Improved Wheat Technologies on Households' Food Consumption in Southeastern Ethiopia. Selected Poster prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, August 18-24, 2012.

Nijkamp, P., & Poot, J. (2005). The last word on the wage curve? A meta-analytic assessment *Journal of Economic Surveys*, *19*(3), 421-450.

Ogundari, K. (2009). A Meta-Analysis of Technical Efficiency in Nigerian Agriculture. Contributed Paper prepared for presentation at the International Association of agricultural Economists Conference, Beijing, China, August 16-22, 2009.

Ogundari, K., & Abdulai, A. (2013). Examining the heterogeneity in calorie–income elasticities: A meta-analysis. *Food Policy*, *40*, 119-128.

Ogundari, K., & Brümmer, B. (2011). Technical efficiency of Nigerian agriculture: A meta-regression analysis. *Outlook on agriculture*, *40*(2), 171-180.

Pattanayak, S. K., Mercer, D. E., Sills, E., & Yang, J. C. (2003). Taking stock of agroforestry adoption studies. *Agroforestry systems*, *57*(3), 173-186.

Rose, A. K., & Stanley, T. D. (2005). A meta-analysis of the effect of common currencies on international trade. *Journal of economic surveys*, *19*(3), 347-365.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272-284.

Slavin, R. E. (1995). Best evidence synthesis: an intelligent alternative to meta-analysis. *Journal of clinical epidemiology*, *48*(1), 9-18.

Stanley, T. D. (2001). Wheat from chaff: meta-analysis as quantitative literature review. *Journal of Economic Perspectives*, 15(3), 131-150.

Stanley, T. D. (2005a). Beyond publication bias. *Journal of Economic Surveys*, 19, 309–345.

Stanley, T. D. (2005b). Integrating the empirical tests of the natural rate hypothesis: a meta-regression analysis. *Kyklos*, 58, 587-610.

Stanley, T. D. (2008). Meta-Regression Methods for Detecting and Estimating Empirical Effects in the Presence of Publication Selection. *Oxford Bulletin of Economics and Statistics*, 70(1), 103-127.

Stanley, T. D., & Jarrell, S. B. (1989). Meta-regression analysis: a quantitative method of literature surveys. *Journal of Economic Surveys*, 19(3), 161-170.

Stanley, T. D., & Jarrell, S. B. (1990). A Meta-Analysis of the Union-Nonunion Wage Gap. *Industrial and Labor Relations Review*, 44(1), 54-67.

Tesfaye, S., Bedada, B., & Mesay, Y. (2016). Impact of improved wheat technology adoption on productivity and income in Ethiopia. *African Crop Science Journal*, *24*(s1), 127-135.

Thiam, A., Bravo-Ureta, B. E., & Rivas, T. E. (2001). Technical efficiency in developing country agriculture: a meta-analysis. *Agricultural economics*, *25*(2-3), 235-243.

Tonitto, C., & Ricker-Gilbert, J. E. (2016). Nutrient management in African sorghum cropping systems: applying meta-analysis to assess yield and profitability. *Agronomy for Sustainable Development*, 36(1), 1-19

WB IEG (2011). *Impact Evaluations in Agriculture: An Assessment of the Evidence*. Washington, DC: The World Bank.

Wu, H., Ding, S., Pandey, S., & Tao, D. (2010). Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching analysis in rural China. *Asian Economic Journal*, *24*(2), 141-160.

Appendix A1:(Table A1) List of studies included in the meta-analysis of impact of improved agricultural technology adoption on welfare in Africa

No	Author(s)	Year of publication	Data used	Countries	Results			Sample size
					Y/E[4]	FS[5]	PO[6]	
1	Kassie et al.	2010	CS	Uganda	100.00		-10.00	945
2	Ahmed et al.	2016	CS	Ethiopia	8.60			301
3	Faltermeier and Abdulai	2008	CS	Ghana	1.95			342
4	Khonje et al.	2015	CS	Zambia	1.94	29.01	-10.28	500
5	Teklewold et al.	2013	CS	Ethiopia	18.90			900
6	Wiredu et al.	2014	CS	Ghana	6.21			150
7	Adekambi et al.	2009	CS	Benin	94.90		-42.40	268
8	Simtowe et al.	2012	CS	Malawi	20.00		-17.40	594
9	Mulugeta and Hundie	2012	CS	Ethiopia	..	477.00		200
10	Nyangena and Juma	2014	PD	Kenya	230.00			1342
11	Bedada and Mesay	2016	CS	Ethiopia	40.10			176
12	Asfaw et al.	2012	CS	Tanzania and Ethiopia	23.70			1313
13	Dercon et al.	2009	PD	Ethiopia	7.10		-9.80	1,477
14	Teklewold et al.	2016	CS	Ethiopia	10.50			929
15	Asfaw and Shiferaw	2010	CS	Ethiopia and Tanzania	0.65			1313
16	Asfaw et al.	2012	CS	Tanzania	0.16		-0.10	613
17	Shiferaw et al.	2014	CS	Ethiopia	..	18.70		2,017
18	Abdulai and Huffman	2014	CS	Ghana	5.27			342
19	Hailu et al.	2014	CS	Ethiopia	8.46			270
20	Melesse	2015	PD	Ethiopia	6.45			2,675
21	Hundie and Admassie	2016	CS	Ethiopia	4.70		-0.38	360
22	Bezu et al.	2014	PD	Malawi	48.00	24.00		1,311
23	Mango et al.	2017	CS	Zimbabwe, Malawi and Mozambique	..	5.49		1,623
24	Zeng et al.	2014	CS	Ethiopia		22.00		791
25	Braun	1988	CS	The Gambia	1.60	4.80		1,249
26	Vigani and Magrini	2014	CS	Tanzania.	204.87	8.00	-2.10	1,543
27	Kinuthia and Mabaya	2017	PD	Uganda and Tanzania	2.92			7,268
28	Smith et al.	2017	CS	Uganda	..	4.50		3,000
29	Afolami et al.	2015	CS	Nigeria	11.95		-5.20	312
30	Awotide et al.	2012	CS	Nigeria	11.50		-5.30	481
31	Challa and Tilahun	2014	CS	Ethiopia	9.31			145
32	Adebayo and Olagunju	2015	CS	Nigeria	9.87			360
33	Wossen et al.	2017	CS	Nigeria	27.50	15.70		2,500
34	Verkaart et al.	2017	PD	Ethiopia	12.60		-3.88	700
35	Mojo et al.	2017	CS	Ethiopia	7.33			305

36	Ogunsumi et al.	2005	TS	Nigeria	62.00			22(years)
37	Omilola	2015	CS	Nigeria	15.40		-1.30	400
38	Benedito	2009	CS	Mozambique	8.45			6,149
39	Amare et al.	2015	PD	Nigeria	5.00	2.00	-0.19	4,062
40	Cunguara and Darnhofer	2011	CS	Mozambique	4.86			6,149
41	Nguezet et al.	2011	CS	Nigeria	46.00		-7.29	481
42	Danso-Abbeam et al.	2017	CS	Ghana	7.70			200
43	Adenuga et al.	2016	CS	Nigeria	..		-18.00	149
44	Sserunkuuma et al.	2005	CS	Uganda	46.10			451
45	Abate et al.	2016	CS	Ethiopia	14.40			490
46	Anissa	2013	CS	Cameroon	8.87		-11.14	1,051
47	Jaleta et al.	2015	CS	Ethiopia	5.73	2.40		2,455
48	Gebrehiwot	2017	CS	Ethiopia	48.00			731
49	Awotide et al.	2015	CS	Nigeria	36.17		-8.48	850
50	Kijima et al.	2008	CS	Uganda	12.00		-5.00	940
51	Beyene et al.	2016	..	Ethiopia	5.50		-3.70	27,835
52	Coulibaly et al.	2016	CS	Malawi	4.78	35.00		338

Notes: Cross-sectional (CS), time series (TS), and panel data (PD).

Source: Compiled by the authors.

[4] Y/E stands for output or expenditure

[5] FS stands for food security levels

[6] PO stands for the poverty index

Appendix A2: List of Studies used for the Meta-Analysis

Abate G.T., Bernard, T., de Brauw, A., & Minot, N. (2016). The Impact of the Use of New Technologies on Farmers' Wheat Yield in Ethiopia: Evidence from a Randomized Control Trial. Selected Paper prepared for presentation at the 2016 Agricultural and Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31-August 2.

Abdulai, A., & Huffman, W. (2014). The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Economics,* 90 (1), 26–43.

Adebayo, O., & Olagunju. K. (2015). Impact of Agricultural innovation on improved livelihood and productivity outcomes among smallholder farmers in Rural Nigeria. *Maastricht School of Management working paper* No. 2015/07.

Adekambi, S. A., Diagne, A., Simtowe, F., & Biaou, G. (2009). The Impact of Agricultural Technology Adoption on Poverty: The Case of, NERICA Rice Varieties in Benin. Contributed paper prepared for presentation at the International Association of Agricultural Economists' conference, Beijing, China, August 16-22, 2009.

Adenuga, A. H., Omotesho, O. A., Ojehomon, V. E. T., Diagne, A., Ayinde, O. E., & Arouna, A. (2016). Adoption of Improved Rice Varieties and its Impact on Multi-Dimensional Poverty of Rice Farming Households in Nigeria. *Applied Tropical Agriculture*, 21(1), 24-32.

Afolami, C. A., Obayelu, A. E., & Vaughan, I. I. (2015). Welfare impact of adoption of improved cassava varieties by rural households in South Western Nigeria. *Agricultural and Food Economics*, *3*(1), 18.

Ahmed, M. H., Mesfin, H. M., Abady, S., Mesfin, W., & Kebede, A. (2016). Adoption of improved groundnut seed and its impact on rural households' welfare in Eastern Ethiopia. *Cogent Economics & Finance*, *4*(1), 1268747.

Amare, M., Cissé, J. D., Jensen, N. D., & Shiferaw, B. (2015). The Impact of Agricultural Productivity on Welfare Growth of Farm Households in Nigeria: A Panel Data Analysis. *FAO. Rome*.

Anissa, B.P. (2016). Impact of Adoption of Improved Rice Varieties on Income and Poverty Reduction among Rice Farmers in Cameroon. Proceedings 59th ISI World Statistics Congress, 25-30 August 2013, Hong Kong.

Asfaw, S., Shiferaw, B., & Simtowe, F. (2010). Does technology adoption promote commercialization? Evidence from chickpea technologies in Ethiopia. In *CSAE 2010 conference on Economic Development in Africa, University of Oxford, UK*.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy,* 37(3), 283–295.

Asfaw, S., Kassie, M., Simtowe, F., & Leslie, L. (2012). Poverty Reduction Effects of Agricultural Technology: A Micro-evidence from Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Asfaw, S., & Shiferaw, B. (2010). Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Poster presented at the 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19 – 23, 2010

Awotide, B.A., Diagne,A., and Omonona, B.T. (2012). Impact of Improved Agricultural Technology Adoption on Sustainable Rice Productivity and Rural Farmers' Welfare in Nigeria: A Local Average Treatment Effect (LATE) Technique. Paper prepared for presentation at the African Economic Conference October 30- November 2, 2012 Kigali, Rwanda.

Awotide, B. A., Alene, A. D., Abdoulaye, T., & Manyong, V. M. (2015). Impact of agricultural technology adoption on asset ownership: the case of improved cassava varieties in Nigeria. *Food Security*, *7*(6), 1239-1258.

Benedito, C. (2009). Assessing the impact of improved agricultural technologies in rural Mozambique. Center of Evaluation for Global Action Working Paper Series Agriculture for Development Paper No. AfD-0917.

Beyene, L. M., Shiferaw, B., Sahoo, A., & Gbegbelegbe, S. (2016). Economy-wide impacts of technological change in food staples in Ethiopia: A macro-micro approach. Partnership for Economic Policy, (PEP), working paper 2016-17.

Bezu, S., Kassie, G. T., Shiferaw, B., & Ricker-Gilbert, J. (2014). Impact of improved maize adoption on welfare of farm households in Malawi: a panel data analysis. *World Development*, *59*, 120-131.

Braun, J.V. (1988). Effects of Technological Change in Agriculture on Food Consumption and Nutrition: Rice in a West African Setting. *World Development*, 16, (9), 1083-1098.

Challa, C., & Tilahun, U. (2014). Determinants and Impacts of Modern Agricultural Technology Adoption in West Wollega: The Case of Gulliso District. *Journal of Biology, Agriculture and Healthcare,* 4(20), 63-77.

Coulibaly, J. Y., Chiputwa, B., Nakelse, T., & Kundhlande, G. (2016). Adoption of agroforestry and its impact on household food security among farmers in Malawi. ICRAF (International Center for Research in Agro-forestry) Working Paper No. 223. Nairobi, World Agro-forestry Centre.

Cunguara, B., & Darnhofer, I. (2011). Assessing the impact of improved agricultural technologies on household income in rural Mozambique. *Food Policy*, *36*(3), 378-390.

Danso-Abbeam, G., Bosiako, J. A., Ehiakpor, D. S., & Mabe, F. N. (2017). Adoption of improved maize variety among farm households in the northern region of Ghana. *Cogent Economics & Finance*, *5*(1), 1416896.

Dercon, S., Gilligan, D. O., Hoddinott, J., & Woldehanna, T. (2009). The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian villages. *American Journal of Agricultural Economics*, *91*(4), 1007-1021.

Faltermeier, L., & Abdulai, A. (2006). The Adoption of Water Conservation and Intensification Technologies and Farm Income: A Propensity Score Analysis for Rice Farmers in Northern Ghana, Annual Meeting, July 27-29, Orlando, Florida, American Agricultural Economics Association.

Gebrehiwot, K. G. (2017). The impact of agricultural extension on farmers' technical efficiencies in Ethiopia: A stochastic production frontier approach. *South African Journal of Economic and Management Sciences*, *20*(1), 1-8.

Hailu, B. K., Abrha, B. K., & Weldegiorgis, K. A. (2014). Adoption and Impact of Agricultural Technologies on Farm Income: Evidence from Southern Tigray, Northern Ethiopia. *International Journal of Food and Agricultural Economics (IJFAEC)*, 2 (4), 91-106.

Hundie, B., & Admassie, A. (2016). “Potential Impacts of Yield-Increasing Crop Technologies on Productivity and Poverty in two Districts of Ethiopia”, in F. Gatzweiler and J. von Braun (eds), *Technological and Institutional Innovations for Marginalized Smallholders in Agricultural Development.* Springer International Publishing (pp. 397-421).

Jaleta, M., Kassie, M., & Marenya, P. (2015). *Impact of improved maize variety adoption on household food security in Ethiopia: an endogenous switching regression approach*. 29th International Conference of Agricultural Economics, ICAE, Milan, Italy 2015.

Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda. *Environment for Development Discussion Paper-Resources for the Future (RFF)*, (10-11).

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, 66, 695–706.

Kijima, Y., Otsuka, K., & Sserunkuuma, D. (2008). Assessing the impact of NERICA on income and poverty in central and western Uganda. *Agricultural Economics*, *38*(3), 327-337.

Kinuthia, B.K., & Mbaya, E. (2017). The Impact of Agriculture Technology Adoption on Farmers’ Welfare in Uganda and Tanzania. Partnership for Economic Policy, number 163, February 2017.

Mango, N., Siziba, S., & Makate, C. (2017). The impact of adoption of conservation agriculture on smallholder farmers’ food security in semi-arid zones of southern Africa. *Agriculture & Food Security*, *6*(1), 32.

Melesse, T. M. (2015). Agricultural technology adoption and market participation under learning externality: Impact evaluation on small-scale agriculture from rural Ethiopia. *Maastricht School of Management* working paper No. 2015/06.

Mojo, D., Fischer, C., & Degefa, T. (2017). The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. *Journal of Rural Studies*, *50*, 84-94.

Mulugeta, T. & Hundie, B. (2012). Impacts of Adoption of Improved Wheat Technologies on Households’ Food Consumption in Southeastern Ethiopia. Selected Poster prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, 18-24 August 2012.

Nguezet, P. M. D., Diagne, A., Okoruwa, V. O., & Ojehomon, V. (2011). Impact of Improved Rice Technology (NERICA varieties) on Income and Poverty among Rice Farming Households in Nigeria: A Local Average Treatment Effect (LATE) Approach. *Quarterly Journal of International Agriculture*, 50 (3), 267-291.

Nyangena, W., & Juma, O. M. (2014). Impact of Improved Farm Technologies on Yields: The Case of Improved Maize Varieties and Inorganic Fertilizer in Kenya. Environment for Development Initiative Discussion Paper Series: EfD DP 14-02.

Ogunsumi, L. O., Ewuola, S. O., & Daramola, A. G. (2005). Socio-Economic Impact Assessment of Maize Production Technology on Farmers' Welfare, in Southwest, Nigeria. *Journal of Central European Agriculture*, 6 (1), 15-16.

Omilola, B., (2015). *The Impact of Agricultural Technology on Poverty Reduction in Africa: Evidence from Rural Nigeria.* Washington DC: Development Strategy and Governance Division International Food Policy Research Institute (IFPRI).

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272-284.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295.

Smith, S. C., Pan, Y., & Sulaiman, M. (2017). Agricultural Extension and Technology Adoption for Food Security: Evidence from Uganda. Institute for International Economic Policy, IIEP-WP-2015-11.

Sserunkuuma, D. (2005). The Adoption and Impact of Improved Maize and Land Management Technologies in Uganda. E*lectronic Journal of Agricultural and Development Economics*, 2(1), 67-84.

Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics*, *93*, 85-93.

Teklewold, H., Mekonnen, A., Kohlin, G., & Di Falco, S. (2016). Does Adoption of Multiple Climate-Smart Practices Improve Farmers' Climate Resilience? Empirical Evidence from the Nile Basin of Ethiopia. Discussion Paper Series August 2016.

Tesfaye, S., Bedada, B., & Mesay, Y. (2016). Impact of improved wheat technology adoption on productivity and income in Ethiopia. *African Crop Science Journal*, *24*(1), 127-135.

Verkaart, S., Munyua, B. G., Mausch, K., & Michler, J. D. (2017). Welfare impacts of improved chickpea adoption: A pathway for rural development in Ethiopia? *Food Policy*, *66*, 50-61.

Vigani, M., & Magrini, E. (2014). Technology adoption and the multiple dimensions of food security: the case of maize in Tanzania. Paper prepared for presentation at the EAAE

2014 Congress 'Agri-Food and Rural Innovations for Healthier Societies', 26-29 August, Ljubljana, Slovenia.

Wiredu, A. N., Asante, B. O., Martey, E., Diagne, A., & Dogbe, W. (2014). Impact of NERICA adoption on incomes of rice-producing households in northern Ghana. *Journal of sustainable development*, *7*(1), 167-178.

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A., & Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of rural studies*, *54*, 223-233.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2014). Agricultural Technology Adoption and Child Nutrition: Improved Maize Varieties in Rural Ethiopia. Selected Paper prepared for presentation at the Agricultural and Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Appendix B1: Supporting Figures

Figure B1

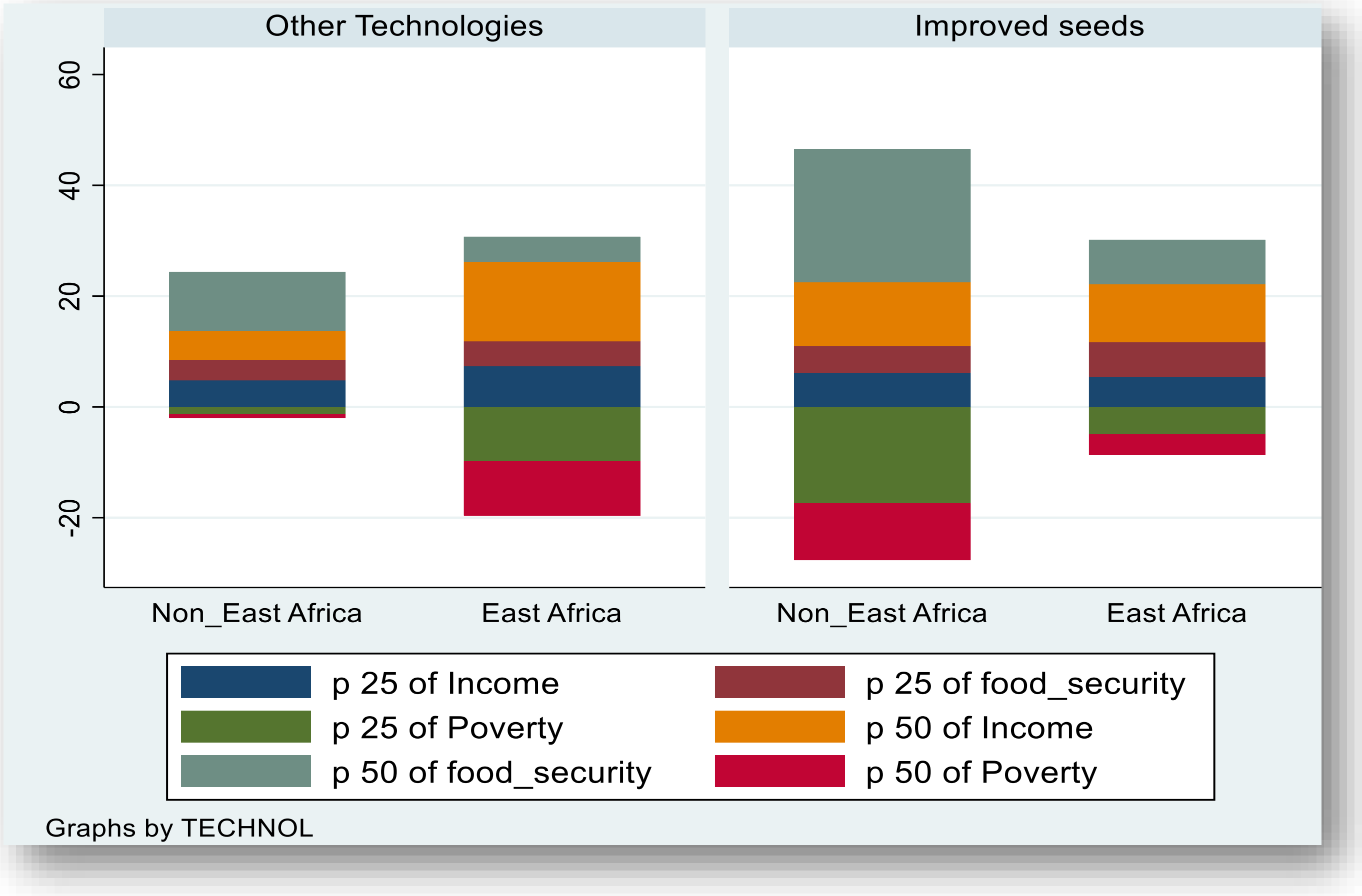


Figure B2

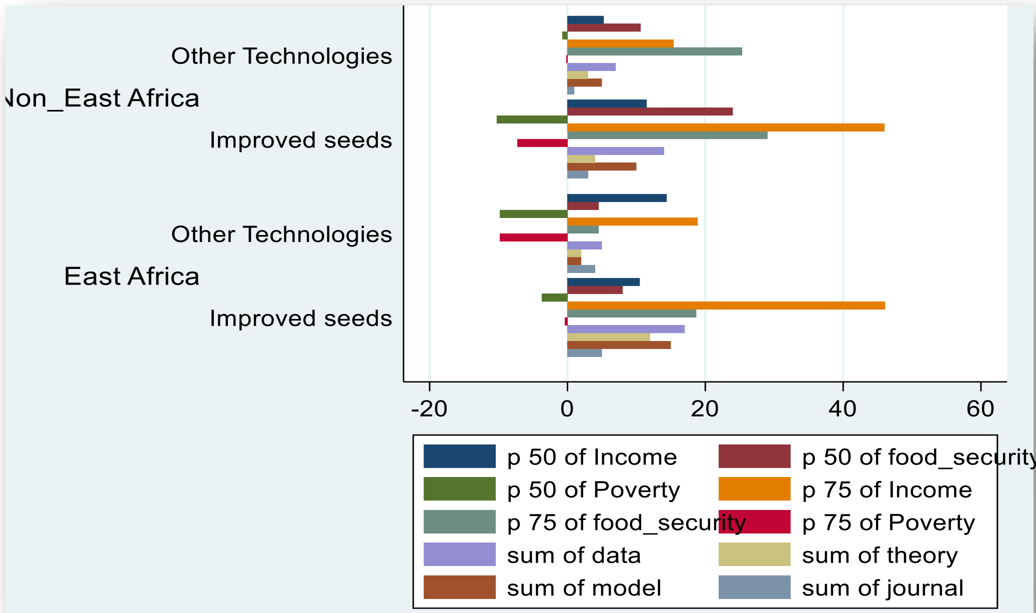
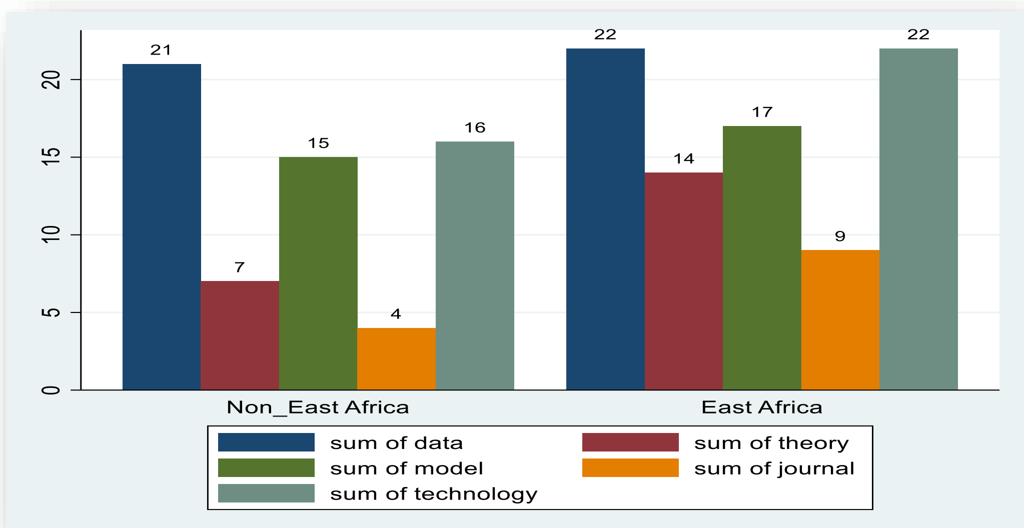


Figure B3.



Appendix Figure B1-B3: Plot of the distribution of the outcomes and moderator variables by region and technology types.

Paper 2: Impact of Improved Agricultural Technology Adoption on Multidimensional Poverty in Rural Ethiopia

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Abstract

A large body of empirical literature has shown that adoption of agricultural technologies reduces poverty. However, these studies use one-dimensional income or expenditure-based measures of poverty which may not reflect other types of deprivations. Therefore, the main objective of this study is examining the impact of adopting improved agricultural technologies on the multidimensional poverty status of rural households in Ethiopia. In this study improved technologies refer to a joint application of row planting methods and use of chemical fertilizers. To estimate the impact of the stated technologies, this study uses propensity score matching and endogenous switching regression methods. To measure the multidimensional poverty index, the study uses the Alkire and Foster counting approach. Using the World Bank's Living Standard Measurement Survey - Wave 3 (data collected in 2015) the results show that adoption of these technologies reduced overall and living standard deprivations. Regionally, a high reduction in deprivation was observed in Amhara region followed by the Oromiya region. The results also show that the impact is significantly higher in the severely deprived households. Finally, this study also sheds light on the effects that technology adoption has on multidimensional poverty reduction.

Keywords: Multidimensional poverty; rural poverty; technology adoption; poverty reduction; Ethiopia

JEL Classification Codes: I30; I32; O10; O33; Q16

1. Introduction

1.1 Background

The introduction of high-yielding technologies during the 1960s and the socioeconomic impact of these innovations in developing countries has been a subject of considerable interest in both theoretical and empirical research. However, while many studies provide detailed descriptions of the experiences in different regions and countries and put forth several arguments to explain the observed behavior and outcomes (which differ among countries, regions, etc.), a rigorous analysis is needed to determine in precise terms the conditions under which these arguments are valid and to specify meaningful relationships among the factors for estimating the causal effects of the new production factor technologies that are adopted (Just and Zilberman,1983).

Agricultural growth and development, and the consequent reduction of poverty and its dimensions, are not possible without yield-enhancing technological options because except in a few areas and under limited circumstances it is no longer possible to satisfy the growing demands of increasing populations by expanding areas under traditional cultivation. Agricultural research and technological improvements and their effective utilization, conditional on investments in human capital, are therefore crucial for increasing agricultural productivity and reducing poverty. This is also necessary for meeting a growing population's demand for food at reasonable prices without a degradation of the natural resource base (Kassie et al., 2010).

Modern and new agricultural technologies and improved practices play a prominent role in increasing agricultural production and hence improving national food security thus reducing poverty in developing countries. When technologies are successfully adopted, they have the potential to stimulate overall economic growth through inter-sectoral linkages and at the same time conserving natural resources (Faltermeier and Abdulai, 2006; Sanchez et al., 2009). As there is a close association between food insecurity, poverty, farming, and environmental degradation, the impact of improved agricultural practices and modern technologies on productivity and the environment has received significant attention in the last few decades.

Hence, the path out of the poverty trap in low-income nations depends on the growth and development of their economically dominating agricultural sector for several reasons, it alleviates poverty through income generation and employment creation in rural areas; helps meet growing food needs driven by rapid population growth and increased welfare and consumption; keeping food prices low, both for urban households stimulating overall economic growth in agriculture-based economies; and conserving natural resources (Kassie et al., 2010).

In much of sub-Saharan Africa (SSA), the agriculture sector is a key fundamental for improving economic growth, overcoming poverty, and enhancing food security, as well as price control in an excess demand situation. However, the sector is mostly dominated by low use of modern technologies and low productivity (Asfaw et al., 2012). This being the case in this region, one of the possible solutions for fighting poverty is through improving productivity, profitability, and sustainability of smallholder farming (The World Bank, 2008). In addition, a high productive agriculture sector facilitates allocation of resources to other sectors, services, and industry, while at the same time maintaining a better-balanced economy.

Similarly, in a region where agriculture is a predominant sector that underpins the livelihoods of most of the poor, adopting more technologies such as new agricultural practices, high-yielding varieties, and associated products such as crop insurance contribute to economic growth and poverty reduction among rural societies and the poor (Kelsey, 2011). According to Ravallion et al. (2007), many poor households in SSA and South Asia live in rural areas where farming is their only livelihood. Their study also shows that almost 75 percent of those living on less than a dollar per day will remain in rural areas till 2040. Similarly, Mendola (2007, p. 373) states, "of the poor people worldwide (those who consume less than a 'standard' dollar-a-day), 75 percent work and live in rural areas. Projections suggest that over 60 percent will continue to do so in 2025." Thus, there is a direct link between poverty reduction and increasing agricultural productivity. This can also create employment opportunities for landless wage laborers.

Recent welfare studies argue that poverty has always been understood as a multidimensional problem especially since Sen's work, even if most of the poverty studies still measure poverty using a one-dimension -- income or expenditure based -- approach. However, over time there has been growing consensus regarding the insufficiency and incompleteness of income poverty measures (Sen, 1992). The first thing to note here is that some important welfare components (poverty status indicators in our case) are not satisfied in the market or that markets function very imperfectly. In such cases, non-market goods or institutions are required to provide for those needs which are not directly captured in one-dimensional poverty measures. The second thing is that each household has a different capacity to convert income into heterogeneous functioning which leads to differing welfare status among households. As Alkire and Santos (2013, p.240) argue the third is, "participatory exercises reveal that poor people describe their state of deprivation using a wide range of dimensions including health, nutrition, lack of adequate sanitation and water, social exclusion, low education, bad housing conditions, violence, shame, and disempowerment. Fourth, income is merely a means to an end. It is the end, which is valuable, not the means."

1.2 Rationale and Motivation

There is a large body of well-established empirical literature that shows that adopting agricultural technologies reduces poverty and food insecurity, leads to an increase in household incomes, raises productivity, gives more opportunities for market access, and leads to an overall increase in social welfare (Adekambi et al., 2009; Asfaw et al., 2012a; Asfaw et al, 2010 ; Ferede et al., 2003; Hundie and Admassie, 2016; Kassie et al., 2010; Mendola,2003, 2007; Mulugeta and Hundie, 2012; Shiferaw et al., 2014; Tesfaye et al., 2016; Wu et al., 2010). Nevertheless, all these studies use unidimensional income or expenditure-based measures of poverty, which may not reflect other types of deprivations as poverty is a multidimensional phenomenon. Departing from the income approach which measures poverty by aggregating shortfalls in incomes from a pre-determined poverty line, a multidimensional index is a numerical representation of the shortfalls in vectors of basic needs from some pre-specified minimum levels.

Alkire and Foster (2007, p.77) argue, “income and consumption indicators reflect material resources that are vital for people’s exercise of many capabilities. The use of monetary indicators alone, however, often reflects an assumption that these indicators are good proxies for multidimensional poverty which implies that people who are consumption poor are nearly the same as those who suffer malnutrition, are ill-educated, or are disempowered. But monetary poverty often provides incomplete measure of poverty and insufficient policy guidance regarding deprivations in other non-monetary dimensions.”[7]

In many cases a one-dimensional income-based measurement of poverty has been used for analyzing poverty in developing countries including those in sub-Saharan Africa and South Asia. Several poverty indices are useful for estimating poverty levels and making inter-temporal and inter-country poverty comparisons. However, some also argue that we need to go beyond these one-dimensional money-metric measures and consider other poverty measurements which include other types of deprivations. There are two arguments when it comes to measuring poverty: the first argument which is more practical relates to the fact that quality in the form of regularity and comparability of income/expenditure data is often poor in many developing countries, especially in sub-Saharan African ones that are generally regarded as showing the most poverty and in extreme forms. The second argument, which is more theoretical and methodological, concerns the multidimensional nature of well-being. Since Sen’s seminal work (1976, 1985, 1992, 1995), well-being and poverty are now seen as a multidimensional phenomenon. Nowadays, there is a renewed interest in a multidimensional approach to poverty since relevant databases are increasingly available which enable comparative methodological and empirical analyses (Bataan, 2008).

Many studies contribute to the debate on the relative importance of ‘direct’ and ‘indirect effects’ of adopting agricultural technologies within poverty alleviation strategies. A large body of existing studies misses many important aspects of poor people’s lives including the diverse ways in which technology directly or indirectly affects their livelihoods. As most of the world’s poor work in agricultural occupations and agriculture is an important sector in most poor countries, new and improved agricultural technologies have an immense role to play making the focus of the current study well-placed. Addressing issues of impact evaluation that most previous research puts less weight on, this study considers endogeneity and the multidimensional nature of poverty. It also uses the multidimensional poverty approach to measure the impact of improved agricultural technologies. This involves using row planting methods and chemical fertilizers together.

Thus, the objective of this research is assessing the role of improved agricultural technology adoption on the multidimensional poverty status of rural households. The empirical question that this research addresses is: Do improved agricultural technologies have the potential to affect households’ multidimensional poverty status? If yes, under what circumstances?

[7] From the summary of S. Alkire and J. Foster’s paper, Counting and multidimensional poverty measures, OPHI Working Paper Series 7, 2007. Available at: www.ophi.org.uk.

Specifically, the study compares the results of measuring multidimensional poverty with those of standard unidimensional approaches for measuring poverty which are based on consumption measures and considers whether the inclusion of additional dimensions leads to a change in a household's poverty level from the standard-based approach. It also accounts for other issues such as weighing the dimensions of poverty used in its aggregation.

The rest of the paper is organized as follows. Section 2 presents a review of literature while Section 3 describes the methodology used for estimating multidimensional poverty and the impact of the stated technology. Section 4 discusses the findings of the study and Section 5 gives the concluding remarks. Section 6 gives the policy implications of the study's findings.

2. Literature Review

2.1 Agricultural technology adoption and Poverty Reduction

A large body of literature has found that adopting agricultural technologies reduces poverty and improves households' well-being in general (Asfaw and Bekele, 2010; Asfaw et al., 2012a; Asfaw et al., 2012b; Kassie et al., 2010; Mendola, 2007; Wu et al.,2010).

Improved agricultural technologies are a key factor in increasing agricultural output and social welfare. Results of numerous studies (for instance, Faltermeier and Abdulai, 2006; Sanchez et al., 2009) show that adoption of improved agricultural technologies can stimulate overall economic growth while also conserving natural resources at the same time. As there exists a strong link between food insecurity, poverty, farming, and environmental degradation the impact of cultivation practices has received significant attention in literature in the last few decades.

The specific contributions of adopting agricultural technologies and their impact on poverty has also been widely documented in economic literature that uses cross-sectional or panel data to evaluate the impact of these technologies and reports that adopting improved technologies significantly reduces poverty (Becerril and Abdulai, 2010; Kassie et al., 2011; Mendola, 2003; Sahu and Das , 2015).

2.2 Poverty

"How we measure poverty can importantly influence how we come to understand it, how we analyze it, and how we create policies to influence it. For this reason, measurement methodologies can be of tremendous practical relevance"

Alkire and Foster (2011b, p.1)

2.2.1 A Unidimensional Measure of Poverty

A traditional mechanism for measuring poverty, standard of living, or quality of life is based on a household unit's aggregate value of a single indicator, monetary income or on its consumption levels (Alkire and Sarwar, 2009). In this approach, a person is defined as poor if his/her income is below a certain per-determined poverty line. The poverty line may be subjective, objective, or hybrid. It is often established as a nationally determined level based on a food or consumption basket or as a percentage of the mean or median overall income distribution. Similarly, traditional measures consider a person or a nation's quality of life in terms of their aggregate income or consumption.

In measuring poverty, a unidimensional method can be applied when a well-defined single-dimensional resource variable such as income, has been selected as the basis for poverty evaluation (Alkire and Foster, 2011b). The assumption in this case is that the single-dimensional indicator variable has a cardinal nature; however, in some cases the variable may only have ordinal significance (that is, the direction of change is discernable, but not its magnitude). On the other hand, measuring a unidimensional environment typically proceeds by setting a poverty line corresponding to a minimum level below which one is considered poor. Aggregation is usually achieved using a numerical poverty measure that determines the overall level of poverty in the distribution given the poverty line.

Till the 1970s, while developing poverty measurement approaches the poor were identified solely based on household income relative to a pre-determined income poverty line. However, around the mid-1970s the 'basic needs' approach argued that developmental concerns should take into account issues of providing people their basic needs instead of just increasing their incomes. This specific method of measuring poverty, combined with other approaches such as social exclusion and Sen's capability approach, called for 'looking at the *actual* satisfaction of basic needs' (Alkire et al., 2015).

However, Bataan (2008), argues that we need to go beyond these money-metric measures and include other additional components of poverty dimensions in measurement processes. The primary reason for this is that the quality (regularity and comparability) of income/expenditures data is often poor in many developing countries especially for those sub-Saharan African countries which are generally regarded as showing the most poverty and extreme poverty. The second reason is that well-being is multidimensional by its very nature.

2.2.2 Multidimensional Measure of Poverty

As Tsui (2002) argues, the concept of multidimensional poverty measurement is not a new one. Apart from the income approach, there are many other alternatives and more direct methods of measuring social welfare. Identifying the poor and checking whether a person meets a set of minimum basic needs or not is the dominant task. Since Sen's influential work (1979, 1985, 1987), poverty has been increasingly recognized as a multidimensional phenomenon. Many factors other than income can provide important information on well-being and poverty such as the state of health, the level of education, ownership of assets, and access to basic services. In such cases, it is not enough to look only at income poverty as we also have to look at other additional attributes.

Alkire (2011) explains that the multidimensionality of poverty is not in dispute. Poverty in its basic context can mean poor health, inadequate education, low income, precarious housing, difficult or insecure work, political disempowerment, food insecurity, and the scorn of the better-offs. The components of poverty change across people, time, and context, but involve multiple domains.

Nowadays the focus of poverty measurement literature has turned from single to multiple dimensions and there exists well-established literature on multidimensional poverty issues (Alkire and Foster, 2007, 2011a, 2011b, 2016; Alkire and Santos, 2014; Atkinson, 2003; Battiston et al., 2013; Bourguignon and Chakravarty, 2003; Maasoumi and Xu, 2015). Sen's (1985, p. 1) work starts with a critique of the traditional welfare approach based on utility. For him, "insofar as opulence and utility have roles, these can be seen in terms of indirect connections with well-being and advantages." In his criticism of utilitarianism, Sen believes that the possession of goods may not translate automatically into well-being, as possession is different from the ability to benefit from the nature of the goods possessed or each person has different capacities to convert possessions into functioning.

As Martinetti (2000, p.208) points out, "what mainly characterizes the capability approach with respect to other multidimensional approaches of well-being is that it is not simply a way to enlarge the evaluative well-being to variables other than income, but it is a radically different way to conceive the meaning of well-being."

3. METHODOLOGY

3.1 Theoretical Framework of the decision to adopt Agricultural Technologies

Agricultural households (farmers) have to face the outcomes of adopting new and improved production technologies that are uncertain (Rahm and Huffman, 1984). Hence, it is assumed that farmer households take adoption decisions based on utility maximization.

There are various technology options available to farmers. In this study the options are either using row planting or opting for a traditional practice. In addition, households also have to take consumption decisions.

Zeng et al. (2015) explain that to characterize a farm household in relation to the impact of adopting a technology, the welfare impact of agricultural technologies primarily occurs through adoption, which is a decision taken by the farmers. Adopters directly feel welfare changes through higher crop yields and reductions in the unit cost of production, which in turn increase their consumption and disposable incomes. These relationships can be quantified using the typical impact evaluation framework in which adoption is seen as a treatment and multidimensional poverty status of farm households as the observed outcome. Let D^* denote the difference between the utility from adoption (U_{1i}) and the utility from non-adoption (U_{0i}) of an improved technology, such that a household i will choose to adopt the technology if $D_i^* = U_{1i} - U_{0i} > 0$. The two utilities are unobserved and unavailable; they can be expressed as a function of observable components in the latent variable model such that a linear relationship can be specified for the ith farm household between the utility derived from the ith technology and the vector of observed firm specific characteristics as:

$$(1) \qquad D_i^* = Z_i\alpha + \varepsilon_i, with \;\; D_i = \begin{cases} 1 & if\ D_i^* > 0\ , new\ technology\ is\ adopted \\ 0 & otherwise\ , old\ technology\ continues \end{cases}$$

where D is a binary 0 or 1 dummy variable for the use of the new technology; D= 1 if the technology is adopted and D = 0 otherwise. α is a vector of parameters to be estimated, Z is a vector that represents multidimensional household and farm-level characteristics, and ε is the random error term. Since the two utilities are non-observable and the net benefit (the difference between the two utilities), D_i, that a farmer gains from adopting is a latent variable determined by observed and unobserved characteristics defined in Equation (1).

There are many important theoretical reasons (and huge empirical literature supporting the theories) why agricultural technologies might improve farm households' well-being. However, less attention has been paid to the differences between the treated and control groups. These differences could be attributed to pre-treatment differences, or agricultural technology adoption may lead to welfare deterioration. Several studies conclude that improved agricultural technologies act in favor of the adopters. However, it should also be noted that adoption may worsen social welfare as well due to some basic factors including regulation costs, investment costs, non-optimal technology choices, harvest failure, climate effects, and other random factors.

3.2 Empirical Modeling of Adoption

This study used a combination of methodologies to ensure the consistency of its results and for checking the robustness of its empirical findings. We used both propensity score matching (PSM) and endogenous switching regression (ESR) methods to evaluate the impact of adopting technologies on multidimensional poverty. The heterogeneity in the decision to adopt or not to adopt a new agricultural technology and the unobservable characteristics of farmers and their farms is controlled by estimating a simultaneous equations model with endogenous switching using the full information maximum likelihood (FIML) estimation method. The non-parametric regression method, PSM is also used for assessing the robustness of the results.

3.2.1 Model Specification

The propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics as:

$$(2) \qquad P(X) \equiv Pr\{D_i = 1|X\} = E\{D_i|X\}$$

where $D_i = \{0, 1\}$ is the indicator of exposure to treatment and X is the multidimensional vector of pre-treatment characteristics.

Rosenbaum and Rubin (1983) show that if the exposure to treatment is random within cells defined by X, it is also random within cells defined by the values of the mono-dimensional variable P(X). As a result, given a population of units denoted by i, the propensity score $P(X_i)$ is known as the average treatment effect on the treated (ATT) which can be estimated as:

$$(3) \qquad \begin{aligned} ATT &= E\{Y_{1i} - Y_{0i} \mid D = 1\} \\ &= E(Y_{1i} \mid D = 1) - E(Y_{0i} \mid D = 1) \end{aligned}$$

where Y_{1i} is the outcome for the treated group and Y_{0i} for the non-treated group. To assess the consistency of the results under different assumptions, this study also used the ESR techniques. Let household welfare be indicated by 'multidimensional poverty status' Y_{1i} for adopters and Y_{0i} for non-adopters. The endogeneity of the adoption decision is accounted for by estimating a simultaneous equations model with endogenous switching using the FIML estimation method. The selection equation for technology adoption is specified as:

(4) $$D_i^* = \beta X_i + U_i, with \quad D_i = \begin{cases} 1 & if\ D_i^* > 0 \\ 0 & otherwise \end{cases}$$

where D_i^* *is* the unobservable or latent variable for technology adoption and D_i is its observable counterpart.

To account for sample selection biases this study uses an ESR model of welfare outcomes where farmers face two situations: (1) adopting a new technology, and (2) not adopting/continuing using the old technology. This is defined as:

(5a) $$\text{Regime 1:}\ Y_{1i} = \alpha_1 X_{1i} + e_{1i} \quad \text{if } D_i = 1$$

(5b) $$\text{Regime 2:}\ Y_{0i} = \alpha_0 X_{0i} + e_{0i} \quad \text{if } D_0 = 0$$

where Y_i, is outcome variables, multidimensional poverty status of households in regimes 1 and 2, X_i represent a vector of exogenous variables thought to influence the multidimensional poverty status of households. Thus, Equations (5a) and (5b) describe the relationship between the variables of interest in each of the two regimes. But the model must be correctly identified. For the model to be identified, the issue of exclusion restrictions is important **(**Di Falco et al., 2011)**,** in which the selection instruments, not only those automatically generated by the non-linearity of the selection model of the technology adoption (Equation 1) but also other variables directly affect the selection variable while at the same time do/do not affect the outcome variable(s) (see Table 14 in the Appendix).

The ESR framework can be used for estimating the average treatment effect of the treated ATT and of the untreated ATU, by associating the expected values of the outcomes of adopters and non-adopters in actual and counterfactual situations. Following literature and Carter and Milon (2005); Di Falco et al. (2011); Shiferaw et al. (2014); and Khonje et al. (2015), we calculate ATT and ATU using the following framework:

Adopters with adoption (observed in the sample):

$(6a)$ $$E(y_{1i} \mid D = 1; X) = \alpha_1 X_{1i} + \sigma_{1\varepsilon}\lambda_{1i}$$

Non-adopters without adoption (observed in the sample)

$(6b)$ $$E(y_{2i} \mid D = 0; X) = \alpha_2 X_{2i} + \sigma_{2\varepsilon}\lambda_{2i}$$

Adopters had they decided not to adopt (counterfactual)

$(6c)$ $$E(y_{2i} \mid D = 1; X) = \alpha_2 X_{1i} + \sigma_{2\varepsilon}\lambda_{1i}$$

Non-adopters had they decided to adopt (counterfactual)

$(6d)$ $$E(y_{1i} \mid D = 0; X) = \alpha_1 X_{2i} + \sigma_{1\varepsilon}\lambda_{2i}$$

where $\sigma_1 and\ \sigma_2$ are the variance of the error term in the selection equation (4) and $\lambda_1 and\ \lambda_2$ are the inverse Mill's ratios(IMRs) computed from the selection equation.

Since Y_{1i} and Y_{0i} are not observed simultaneously the covariance between e_{1i} and e_{0i} is not defined (Maddala, 1983, p.224 and Lokshin and Sajaia, 2004). An important implication of the error structure in ESR approach is that because the error term of the selection equation (4) u_i is correlated with the error terms of the outcome equation (5a) and (5b) (e_{1i} and e_{0i}), the expected values of e_{1i} and e_{0i} conditional on the sample selection are nonzero **(**Di Falco et al., 2011);

$$E[e_{1i} \mid D_i = 1] = \sigma_{e1u}\frac{\phi(\beta X_i)}{\Phi(\beta X_i)} = \sigma_{e1u}\lambda_{1i} \quad \text{and}$$

$$E[e_{0i}|\ D_i = 0] = -\sigma_{e0u}\frac{\phi(\beta X_i)}{1-\boldsymbol{\Phi}(\beta X_i)} = \sigma_{e0u}\lambda_{0i}$$

where $\boldsymbol{\phi}$(.) is the standard normal probability density function, $\boldsymbol{\Phi}$(.) the standard normal cumulative density function, and $\lambda_{1i} = \frac{\phi(\beta X_i)}{\Phi(\beta X_i)}$ and $\lambda_{0i} = \frac{\phi(\beta X_i)}{1-\Phi(\beta X_i)}$.

where $\lambda_{1i}\, and\, \lambda_{0i}$ are the inverse Mill's ratios (IMRs) computed from the selection equation(4),and will be included in 5a and 5b to correct for selection bias in a two-step estimation procedure.

Equation (6a) and (6b) represent the actual expectations observed from the sample, while equation (6c) and (6d) are the counterfactual expected outcomes. The ATT is computed as the difference between Equations (6a) and (6c) as:

(7) $$ATT = (a) - (c) = E(y_{1i}\ |D = 1; X) - (y_{2i}\ |D = 1; X)$$
$$= X_{1i}(\alpha_1 - \alpha_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon})$$

Similarly, the expected change in non-adopter's multidimensional poverty status had they been treated, which is the average treatment effect on the untreated (ATU) is given by the difference between Equations (6d) and (6b) as:

(8) $$ATU = (d) - (b) = E(y_{1i}\ |D = 0; X) - E(y_{2i}\ |D = 0; X)$$
$$= X_{2i}(\alpha_1 - \alpha_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon})$$

3.3 Poverty Analysis

3.3.1 Unidimensional Analysis of Poverty

3.3.2 Theoretical Framework for a Unidimensional Poverty Analysis

Even though poverty is a multifaceted phenomenon, dominant portions of literature on poverty focus on single dimension indices. To explore the extent of unidimensional poverty and comparing it with the multidimensional approach to poverty measurement in rural Ethiopia this study uses a more general class of poverty measurement approach proposed by Foster et al. (1984) which is easily decomposable into different sub-groups.

A unidimensional measurement of poverty is suggested when a well-defined single-dimensional indicator variable, like income or consumption level, has been selected as the basis for poverty evaluation (Alkire and Foster, 2011b). This method also requires a single dimensional variable and a single cut-off but places no *a-priori* restrictions on how the dimensional indicator variable has been constructed. This proposed dimension indicator variable which is assumed to be cardinal may sometimes only have ordinal values. In this approach of poverty measurement, identifying the poor in general is done by setting a threshold corresponding to a minimum level below which the ith unit is considered poor. Again, aggregation is typically achieved through the application of a numerical poverty measure that determines the overall level of poverty in a distribution given the poverty line. Now, let the dimension indicator variable of household i be y_i and z be the poverty line, while n and q stand for the total population and the total number of poor in the population respectively, and α is the poverty aversion parameter. Then the unidimensional poverty index, p_α , can be expressed as:

(9) $$p_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left\langle\frac{z-y_i}{z}\right\rangle^{\alpha}$$

when α = 0, P_0 is simply the headcount ratio, the proportion of people at and below the poverty line. The *deprivation vector* g^0 replaces each dimensional indicator's variable at and below the poverty line with 1 and replaces non-poor with 0. If α = 1, P_1 is the poverty gap index (or depth of poverty), defined by the mean distance to the poverty line where the mean is formed over the entire population with the non-poor counted as having a zero-poverty gap. Then the *normalized gap vector* g^1 replaces each poor income dimensional indicator y_i with the normalized gap $(z - y_i)/z$ and assigns zero to the rest. Finally, when α = 2, P_2 is the squared poverty gap (severity of poverty index). The *squared gap* vector g^2 replaces each poor dimensional indicator with the squared normalized gap $[(z - y_i)/z]^2$ and assigns zero to the rest.

Now the headcount ratio can be given as $p_0 = \eta(g^0)$, or the mean of the deprivation vector; this indicates the prevalence of poverty (Alkire and Foster, 2011b). Similarly, the poverty gap measure is $p_1 = \eta(g^1)$ and it measures the average depth of poverty across the population of interest. The squared gap can also be expressed as $p_2 = \eta(g^2)$. Sometimes it is called distribution sensitive FGT and it focuses on the conditions of the poorest of the poor.

3.3.3 Theoretical Models for measuring Multidimensional Poverty

For measuring multidimensional poverty this study used Alkire and Foster's (2007, 2011a) counting approach which follows the method of aggregation proposed by Foster et al. (1984), FGT, which is built on the same family of measures. This family satisfies a certain number of axioms such as decomposability. Following this framework, a counting approach of multidimensional poverty can be developed as:

Consider a population of n individuals. Let d ≥ 2 be the number of dimensions and $x = [x_{ij}]$ the n x d matrix of achievements, where x_{ij} is the achievement of individual i (i = 1, ..., n) in dimension j (j = 1, ..., d). x has the following form:

$$x = \begin{bmatrix} x_{11} & \cdot & x_{1j} & \cdot & x_{1d} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{i1} & \cdot & x_{ij} & \cdot & x_{id} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{n1} & \cdot & x_{nj} & \cdot & x_{nd} \end{bmatrix}$$

In this case, it should be noted that each row vector x_i represents individual i's achievements, while each column vector x_j gives the distribution of dimension j's achievements across the set of individuals.

Let $|z_j| > 0$ be the indicators' cut-off below which a person is deprived in indicator *j*. x_i is the row vector of individual *i*'s achievements in each dimension, and x_j is a column vector of dimension *j* achievements across the set of individuals; thus x_{ij} is the achievement of individual i in dimension j.

Identification of the Poor

The first step in measuring poverty is identifying who is poor. Sen (1976) identified two major issues in the measurement of poverty: identifying those who are poor and aggregation of information about poverty across society. In a single dimension of income or consumption-based approach, identifying who is poor is relatively straightforward. An income or consumption poverty line is the level of the dimension indicator variable necessary for purchasing a basic basket of goods and services, which divides the population in to poor and non-poor. In the multidimensional context, however, the identification of who is poor is more complex than the single dimension approach (Alkire and Foster, 2011a). The Alkire and Foster approach combines a method of identifying the poor based on counting the number of (weighted) deprivations on achievements and a method for aggregation based on an extension of the unidimensional FGT family of measures to the multidimensional context.

If all dimensions are equally weighted, suppose that a matrix of deprivations $\tilde{x}^0 = [\tilde{x}_{ij}^0]$ is derived from *x* as follows:∀ i and j:

(10) $$\tilde{x}_{ij}^0 = \begin{cases} 1 & if\ x_{ij} < z_j \\ 0 & otherwise \end{cases}$$

This implies that if $\tilde{x}_{ij}^0$= 1 then individual *i* is deprived in dimension j and $\tilde{x}_{ij}^0$= 0 otherwise. A horizontal summation of each row of $\tilde{x}^0$ gives us a column vector c of the deprivation count containing c_i ,the number of deprivations suffered by individual i.

Assuming that all the dimensions are equally weighted, the weighted deprivation gap ($w_j \tilde{x}_{ij}^0$) for each indicator, finding the aggregate deprivation score for each individual (c_i) is constructed as the horizontal sum of weighted deprivation gaps for each individual given as:

(11) $$c_i = \sum_{j=1}^{d} w_j \, \tilde{x}_{ij}^0$$

where w_j is the weight attached to each indicator.

For identifying, consider the identification function $\rho(x_i, z)$ such that:

(12) $$\rho(x_i, z) = \begin{cases} 1\ if\ individual\ i\ is\ multidimensionally\ poor \\ \qquad 0\ otherwise \end{cases}$$

As Alkire and Foster (2007, 2011a) explain, there are two identification methods in this poverty analysis: the union and intersection approaches. In the union method, person i is said to be multidimensionally poor if there is at least one dimension in which the person is deprived [that is, $\rho(x_i, z) = 1$ if and only if $c_i \geq 1$]. But, if many dimensions are considered, the union approach will often treat most of the population as being poor, including persons who are not considered poor. Thus, a union-based poverty methodology may not always be an efficient method for distinguishing and targeting the most deprived persons. Therefore, it is not appropriate in all circumstances.

We can use the other extreme case, the intersection method, which identifies person i as poor only if the person is deprived in all the variables of the dimension indicator [that is $\rho(x_i, z) = 1$ if and only if $c_i = d$]. However, this method unavoidably eliminates some units that are in poverty, but not universal deprivation (for example, a person with insufficiency in every other dimension who happens to be healthy). Alkire and Foster (2011a, p.478) argue that "this creates a different tension-that of considering persons to be non-poor who evidently suffer considerable multiple deprivations." Thus, the Alkire-Foster (2007, 2011a) methodology proposes identifying the poor based on both the union and intersection methods with moderate possibilities of varying cases based on additional interests.

A normal and reasonably good approach of identifying the poor is using a value of the cut-off level for c_i that ranges somewhere between the two extremes of 1 and d. Let k be the cut-off. Parameter k is called the poverty cutoff and it ranges from the minimum weight assigned to any indicator, union criterion, to the total number of considered indicators, the intersection criterion. For k=1…. d, let ρ_k be the identification method defined by $\rho_k(x_i; z) = 1$ if $c_i \geq k$, and $\rho_k(x_i; z) = 0$ if $c_i < k$.We see here that ρ_k identifies person i as poor when the number of dimensions in which i is deprived is at least k; otherwise, if the number of deprived dimensions falls below the poverty cut-off k, then i is not poor (Alkire and Foster, 2011a; Alkire and Santos, 2013). This shows that as ρ_k is based on both the within dimension (deprivation) cut-offs z_j and the across dimension or poverty cut-off k, it is referred to as ρ_k as the dual cut-off method of identification and note also that ρ_k includes the union and intersection methods as special cases where $k = 1$ and $k = d$ (Alkire and Foster, 2009). The dual cut-off method has several advantages.[8] Once we have identified the poor (deprivation status of each unit), the next step is assigning weights to each dimension.

We assigned an equal weight across dimensions and the same weights to all indicators j within each dimension. This was done by assuming that the available chosen dimensions are relatively equally important (Alkire and Foster, 2011a).

As the final step, we need to estimate the MPI for both the poor and non-poor households. Following the methodology developed by Alkire and Foster (2011a) we can compute MPI applying the next steps.

The Multidimensional poverty measures

Let $M(x; z)$ be the class of multidimensional poverty measures proposed by Alkire and Foster (2007). Applying the method proposed by the AF family of multidimensional poverty, we have two basic parts to be computed: the first measure is given by the headcount ratio (H), which is the proportion of incidence (depth) of people who experience multiple deprivations and is gives as:

[8] See Alkire and Foster (2007, 2009, 2011a) for more characteristics of the dual cut-off method.

$$H = \frac{q}{n}$$

And the *average deprivation shares* across the poor by (the intensity or breadth of poverty) (A) is the average deprivation score of those poor segments of the population:

$$A = \frac{\sum_{i=1}^{n} \frac{1}{d} (c_i)}{q}$$

The second measure combines H and A to obtain an expression satisfying dimensional *monotonicity* (unlike H). The new measure M_0 called the *adjusted headcount ratio* is given by the product of the above two terms (H x A) as:

(13) $$M_0(x; z) = H \times A = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{d} (c_i)$$

Note also that the remaining classes of multidimensional poverty indices can be computed in a similar way by simply varying the values of α in the general setting, $M_\alpha(x; z)$ .When α = 1, the measure M_1 is called the adjusted poverty gap and if α=2 the measure M_2 is called the adjusted squared poverty gap.

Decomposability and Dimensional Break-Down of MPI

Decomposability implies that overall poverty is a population share weighted average of sub-group poverty levels. All members of the M_α family can be disaggregated/ decomposed into its components (Alkire and Santos, 2013). Thus, overall poverty can be decomposed across different population sub-groups.

Here each measure can be expressed as the weighted sum of individual poverty, where each person has a relative weight of $1/n$:

(14) $$M_\alpha(x; z) = \frac{1}{n} \sum_{i=1}^{n} \left\langle \frac{1}{d} \sum_{j=1}^{d} x_{ij}^{\alpha} (k) \right\rangle$$

So, if we have a population sub-group I, its contribution to overall poverty can be expressed as:

(15) $$C_I = [(n_I/n) M_\alpha^I]/M_\alpha$$

where (n_I / n) and M_α^I are the population share and the poverty measure of sub-group I respectively, and M_α is the poverty measure of the overall population. As Alkire and Santos (2013, p.245) state, “Whenever a region’s contribution to poverty or some other group widely exceeds its population share, this suggests that there is a seriously unequal distribution of poverty in the country, with some regions or groups bearing a disproportionate share of poverty. Clearly, the sum of the contributions of all groups needs to be 100 percent.”

3.4 Data Sources and Variables' Measurements

The analysis in this study is based on cross-sectional data obtained from the World Bank's Living Standard Measurement Survey-Integrated Surveys on Agriculture (LSMS-ISA): Ethiopia Socioeconomic Survey (ESS)-Wave 3 (2015). The data targeted the rural parts and small and medium towns in the country. The survey covered around 4,954 households drawn from the nine regional states and two city administrations. Households from both small and medium towns were excluded because of non-applicability of agricultural technology adoption after which the sample size became 3,727. After adjusting and accounting for missing variables and values, the final sample used in the study is 2,752 households across the regions of the country. The dataset has good qualities as it contains information regarding income or consumption expenditure, so we are able to assess how the inclusion of additional dimensions of poverty affect our measurement of poverty following the MPI approach and comparing this with the monetary approach.

We assigned an equal weight across dimensions and the same weights to all indicators within each dimension. This was done by assuming that the available chosen dimensions were relatively equally important.

The focus of this study is the impact of improved agricultural technologies on multiple rural dimensions of poverty. Unfortunately, the data does not contain information on the health dimension attributes of child mortality and nutrition. To address this problem, we used parental consultation and physical or mental disability indicators to represent the health dimension. Similarly, there is no information on one indicator of education, child school attendance, in the dataset so we used reading and writing abilities of any household member as a possible proxy.

The outcome variables of interest in our study are the composite MPI score and its three dimensions. We computed these values by following the methodology developed in Alkire and Foster (2007, 2011a). The multidimensional index ranges between 0 and 1, where 1 means total deprivation in every indicator and 0 denotes no deprivation in any indicator. The index is computed with a bundle of equally weighted dimensions –health, education, and living standards– sub-divided into 10 indicators in our case, but the number of dimensions or indicators can vary based on objectives and other interests (Table 1).

Table 1: MPI's Dimensions, Indicators, Deprivation cutoff, and Weights

Dimension	Indicator	Deprived if -----------------------	Weights
Education	Years of Schooling	No household member aged 10 years or older has completed 6 years of schooling	1/6
	Read and write	No household member can read and write in any language	1/6
Health	Parental consultation	No household member has consulted any medical assistant for the last 12 months	1/6
	Disability	Any household member is disabled due to a non-accident cause	1/6
Living Standard	Electricity	The household has no access to electricity	1/18
	Improved sanitation	The household's sanitation facility has not improved (according to MDG guidelines), or it has improved but is shared with other households	1/18
	Improved drinking water	The household does not have access to improved drinking water (according to MDG guidelines) or safe drinking water is at least a 30-minute walk from home, round trip	1/18
	Flooring	The household has a dirt, sand, or dung type of floor	1/18
	Cooking fuel	The household cooks with dung, wood, or charcoal	1/18
	Assets ownership	The household does not own more than one radio, TV, telephone, bicycle, motorbike, or refrigerator and does not own a car or truck	1/18

Source: Alkire and Santos (2010); MDGs.

4. EMPIRICAL RESULTS

4.1 Descriptive Analysis

This section gives the descriptive statistics of our poverty analysis. The first part presents a unidimensional measure which is followed by a descriptive statistical analysis of poverty using different multidimensional poverty estimation results at the household level.

We use consumption expenditure in the unidimensional approach and the poverty analysis is done at the household level. We used the national poverty lines developed by MoFED (2012) to estimate the poverty index. The estimated unidimensional consumption expenditure-based poverty analysis shows that about 42 percent of the households were poor in the country (see Table 2 in the Appendix).

Concerning the adoption status of households, adopters of technology were slightly better off than the non-adopters. The incidence of poverty was higher among non-adopters (42.1 percent) than among adopters (41.6 percent) which implies that adopters were better-off due to the 'technology impact'. A comparison between sexes showed that female headed households were less impoverished than male headed ones. This result shows that 42.3 percent of male headed households were under poverty while only 40.1 percent of the female headed households were impoverished.

A region-wise comparison showed that the status of poverty differed from one region to the other once. Benishangul was the most impoverished region (59 percent) followed by SNNP (57.1 percent), and Amhara (49.5 percent). On the other hand, in Dire Dawa the incidence of poverty was the lowest (3.30 percent) followed by Harari (14.2 percent). These poverty levels were much higher than the national poverty rate; the government's official reports maintain that nationally the incidence of poverty was only about 24 percent in 2015-16 (MoFEC, 2017).

To consider heterogeneity among different social groups, mainly differentiated by adoption status, gender, and regional location, a heterogeneous poverty line was constructed using the median of consumption expenditure. The estimated poverty based on an analysis of the relative poverty line of median consumption expenditure showed that about 47.2 percent of the households were poor. This result shows that more poor were found using the relative poverty line as compared to the results using the absolute poverty line which applies to every group regardless of its initial conditions.

Similarly, comparisons across different groups also showed an increase in poverty when we used the relative poverty line. For example, about 41.6 percent of the adopters were poor in the case of the absolute poverty line, but this increased to 46.8 percent when the relative poverty line was applied. Male-headed households' poverty status increased from 42.3 to 48.2 percent as a result of using the relative poverty line. Concerning regional distribution of relative poverty, the Benishangul region had the highest poor population (64.6 percent) followed by Amhara and SNNP with 57.7 and 56.0 percent poor population respectively. The high relative poverty rates suggest that high levels of inequalities in rural consumption.

[Insert Table 2 about here]

It is also important to check the matching quality of the model. Before estimating the causal effects of the technologies, we tested the matching quality. The matching methods were tested, and they passed different quality checking tests. After estimating the propensity scores for the adopter and non-adopter groups, the common support condition was checked. We used the standardized bias reduction and joint significance and pseudo-R^2 tests. The covariate balancing tests before and after matching are reported in Table 3 in the Appendix. The standardized mean difference for overall covariates used in the propensity scores for the two outcome variables, the total deprivation score and the living standards deprivation score, was between 35.2-48.8 percent before matching and the value reduced below 5 percent after matching.

The p-values of the likelihood ratio tests showed that the joint significance of the covariates was always rejected after matching, whereas it was never rejected before matching. The pseudo R^2 also dropped significantly from around 19.5 - 20.4 percent before matching to about 0.1 - 0.7 percent after matching under the two outcome variables. The likelihood ratio test was also statistically significant before matching but became insignificant after matching. The low pseudo R^2, high bias reduction, and the insignificant p-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score is successful in terms of balancing the distribution of covariates between the adopter and non-adopter groups.

[Insert Table 3 about here]

After this review and description of the state of conventional poverty levels of households in different categories, we present the multidimensional poverty status of households disaggregated into different household groups. The study used the AF's three dimensions and 10 indicators approach for estimating different forms of multidimensional poverty indices. Table 4 gives the summary of MPI's dimensions and indicators for the entire sample. The results show that people were the most deprived in the education dimension (41.8 percent) followed by the standard of living dimension (34.6 percent). It also shows that people were also deprived in the health dimension (about 24 percent). Indicator-wise, people were the most deprived in terms of years of schooling (24.6 percent) while they were less deprived in access to clean water (3.2 percent).

Table 4: Summary of MPI's dimensions and indicators

Dimension	Indicator	MPI	
Education			0.418
	Years of schooling	0.246	
	Read and write	0.172	
Health			0.236
	Consultation	0.183	
	Disability	0.054	
Standard of Living			0.346
	Electricity	0.066	
	Sanitation	0.035	
	Water	0.032	
	Floor	0.087	
	Fuel	0.086	
	Assets	0.038	

Source: Author's computations using WB LSMS data (2015), (2018).

Table 5 gives the MPI for different household groups (decompositions). One of the advantages of using MPI for measuring poverty is that it can be disaggregated into different household groups, dimensions, or indicators. First, we disaggregated it into adopter and non-adopter categories, then by sex, and finally by region.

The results in Table 5 show that the adopters were less deprived in all the dimensions, except health status, implying that technology adoption improved social welfare (even though a further evaluation of the actual impact needs to be done; this issue is covered later). The estimated multidimensional headcount ratio (H) and the adjusted multidimensional headcount ratio (MPI or Mo) are reported for both adopters and non-adopters and the results are almost similar for the two groups with a slightly higher poverty rate for non-adopters in terms of adjusted multidimensional headcount ratio (59.8 percent as compared to 56 percent) for the adopter group.

When it comes to the contribution of each dimension, the results show that both adopter and non-adopter households were most deprived in the education dimension while health deprivation was the lowest in both categories supporting the results of the entire sample (also see figure 1 where the results are disaggregated by gender).

Our analysis by male and female-headed households also shows that gender differences in poverty status were significant. Male-headed households were less deprived as compared to female-headed ones in both the multidimensional headcount ratio (94.75 percent versus 97.4 percent) and the adjusted multidimensional headcount ratio (56.6 percent versus 66.0 percent). In terms of the contributions of each domain, like the cases observed earlier, the education dimension showed higher differences between male and female headed households. Figure 1 also shows the contribution of adopters and non-adopters to aggregate MPI disaggregated by sex, and the results support the findings presented in Table 5 showing that both adoption categories had an almost similar status in most cases.

Table 5: MPI's dimensions and indicators (by sub-groups)

Dimension/ indicator	Adoption Status			Sex		
	Adopter	Non-Adopter	Total	Male	Female	Total
Indices by sub-group						
H	0.943	0.949	0.947	0.940	0.974	0.947
Mo	0.560	0.598	0.586	0.566	0.660	0.586
Pop. Share	0.311	0.689	1.00	0.784	0.216	1.00
Contribution of each domain (dimension, percent)						
Education	0.417	0.418	0.418	0.404	0.462	0.418
Health	0.238	0.236	0.236	0.240	0.226	0.236
Standard of Living	0.345	0.346	0.346	0.356	0.312	0.346

Source: Author's computations using WB LSMS data (2015), (2018).

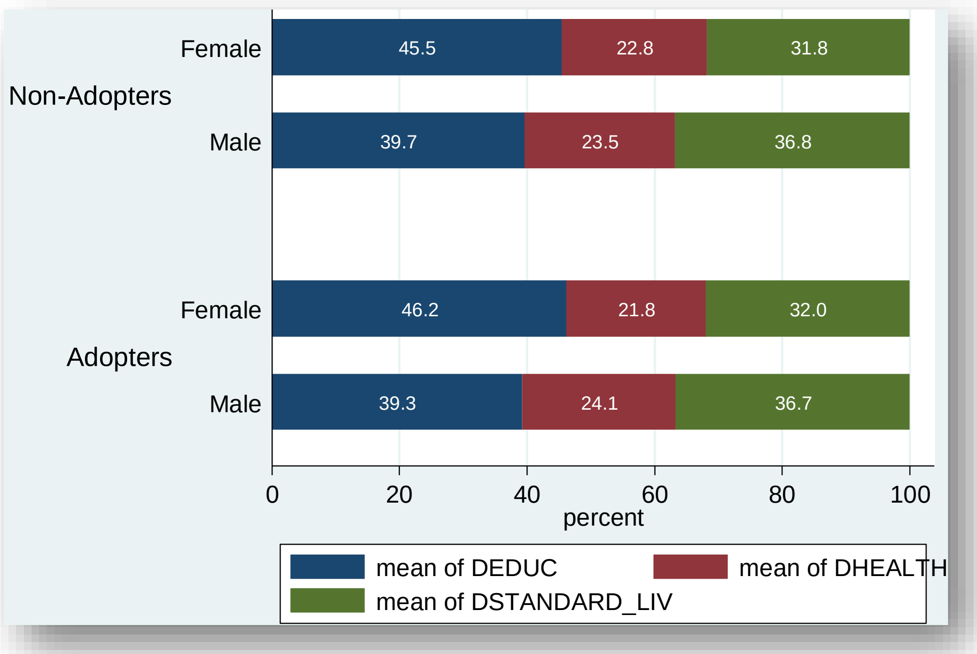

Figure 1: Contribution of each MPI domain to total deprivation across adoption categories by sex

Note: DEDUC, DHEALTH, and DSTANDARD_LIV stand for education, health, and living standard deprivations respectively

Looking at the health dimension, male-headed households registered a higher MPI than female-headed households. The basic reason for female-headed households having a low MPI as compared to the male headed group in the health dimension is that the current national health policy focuses on women and children's healthcare. This result supports conventional poverty outputs where female headed households register lower values in the headcount index.

Concerning the standard of living component of MPI, male-headed households contributed more to poverty. As can be seen from Table 5, about 36 percent of them were deprived in the standard of living, while female headed households were slightly less deprived (31.2 percent). The table also shows that female headed households had better access to asset holdings.

The third disaggregation that we followed was the decomposition of MPI by regions in the country (see Table 6). To acknowledge the advantages of the multidimensional poverty approach, we also used MPI's regional disaggregation. A further disaggregation of MPI gives us more room to see the distribution and extent of the multidimensional poverty situation in different regions of the country. A closer look at the adjusted multidimensional headcount ratio (Mo), under the indices in the sub-group column, shows that the three most deprived regions were Somalie, Afar, and Amhara with Mo values of 66.2, 65.8, and 63.7 respectively in percentage points.

Except for these three regions, on average, the adjusted multidimensional headcount ratio was almost equally distributed among the remaining seven regions. In terms of contribution to overall poverty in the country, the highest proportional poverty was registered in SNNP followed by Amhara and Oromiya regions. Except SNNP, Amhara, and Oromiya the remaining regions had a small number of inhabitants and made a small contribution to aggregate poverty. Like the results given in Table 6, Figure 2 (see Appendix) also shows the contribution of each component of MPI in the aggregate deprivation score in each of the 10 regions and the results support the findings reported in Table 6.

Table 6: MPI's Decomposition by Regions

Region	**MPI**							
	Indices by sub-group (absolute)			Contribution of sub-groups to indices (percent)		Contribution of each domain (percent)		
	H	Mo	Pop Share	H	Mo	Educ	Health	Living stad
Afar	0.990	0.658	0.009	0.010	0.011	0.431	0.169	0.400
Amhara	0.977	0.637	0.216	0.223	0.235	0.431	0.231	0.338
Benishan	0.949	0.511	0.034	0.035	0.030	0.468	0.185	0.347
Dire Daw	0.895	0.563	0.037	0.035	0.035	0.476	0.203	0.321
Gambella	0.922	0.556	0.031	0.030	0.030	0.423	0.243	0.334
Harari	0.917	0.536	0.038	0.037	0.035	0.456	0.225	0.318
Oromiya	0.940	0.576	0.202	0.200	0.198	0.379	0.260	0.361
Somalie	0.992	0.662	0.042	0.044	0.047	0.411	0.208	0.381
Tigray	0.945	0.576	0.107	0.107	0.105	0.416	0.214	0.370
SNNP	0.936	0.567	0.284	0.281	0.275	0.418	0.251	0.331
Total	0.947	0.586	1.00	1.00	1.00	0.418	0.236	0.346

Source: Author's computations using WB LSMS data (2015), (2018).

Next, we compared the conventional approach to multidimensional approaches. More deprived households were found following the multidimensional approach (58.6 percent) as compared to the consumption-based absolute poverty approach (42 percent) using the absolute poverty line; this figure was 47.2 percent when the relative poverty line is used.

4.2 Econometric results

Like the descriptive section, this econometric section starts with an analysis of the conventional poverty approach. Once we had estimated the propensity scores and checked their matching quality, we computed the ATT of the outcome variables, consumption expenditure, and headcount ratio, for comparing these with the multidimensional approach to poverty, which is the main interest of this research. We used four commonly used matching algorithms --- the nearest neighborhood matching (NNM), kernel matching (KM), radius matching (RM), and stratified matching (SM). The estimated results based on the first three matching algorithms are reported in Table 7. The results show that adoption had a positive and significant effect on consumption expenditure and a negative impact on poverty as measured by the headcount ratio.

Table 7: Impact of technology adoption on Unidimensional poverty indicators

	Outcome variables	Outcome mean		ATT
		Adopters	Non-adopters	
NNM	Consumption expenditure	5,449.38	5246.04	203.34(2.64)***
	Headcount ratio	0.3817	0.3830	-0.0020(-1.72)**
KM	Consumption expenditure	5,449.38	5,297.29	152.09(1.93)**
	Headcount ratio	0.3817	0.3842	-0.0025(-1.57)*
RM	Consumption expenditure	5,449.38	5,262.14	187.24(2.24)***
	Headcount ratio	0.3817	0.3848	-0.0031(-1.74)**

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. T-statistics in parenthesis.

Source: Author's computations using WB LSMS data (2015), (2018).

The average welfare (per capita consumption expenditure) gains of adopted technology ranged from Birr 152 to Birr 203 under the three matching methods and the estimated gains were statistically significant. The estimated results measured the average differences in consumption expenditure of the same pairs of households in all pre-treatment characteristics, but having different technological status based on adopting and not-adopting the stated technology. The specific matching algorithm that we used found that the estimated impacts of technology adoption on poverty reduction as measured by the headcount index ranged between 0.20 - 0.31 percent and they were all statistically significant. The values of the headcount index under 'outcome mean' were a bit lower than what we obtained in the descriptive analysis. A possible reason for this is that in this part some non-matched samples were removed from both the adopter and non-adopter groups which led to a reduction in the mean values. The estimated impact on the headcount index is very low which may be due to the fact that the conventional poverty approach cannot reflect the actual impact of the adopted technology on non-monetary welfare gains such as health, quality of life, and education attainments. So, we need an approach that shows the complete impact of technology on social welfare. Here the best alternative is the multidimensional approach to poverty.

In the main part of the analysis we looked at the impact of the adopted technology on multidimensional poverty on each of the deprivation indicators – overall, education, health, and living standards. Using Equation (11) we computed the aggregate deprivation score.[9] For overall deprivation and each dimension, we separately estimated the impact of the specified technology on households' multidimensional poverty using the aggregate deprivation score as an outcome variable using both PSM and ESR models.

Table 8 gives the results of PSM under the three matching methods for the overall (composite) multidimensional deprivation. The ATT term is negative in all the matching methods and statistically significant suggesting that adopter households' multidimensional poverty declined between 2.0 and 3.0 percent. These results remain consistent even when different matching algorithms are used suggesting that there is a negative effect of being an adopter of the specified technology on the multidimensional poverty weighted score. In the results, a radius matching method reported the highest decrease in the overall multidimensional poverty indicator while kernel-based matching with a band width of 0.03 reported the lowest value.

The results also show that the adopters were better-off because of the adopted technology as compared to their counterfactual group supporting the descriptive statistics' results, but in the multidimensional approach the impact is higher and relatively complete in coverage. The possible reason for the higher reduction in poverty in this section is the inclusion of additional indicators of poverty which were not considered in the conventional approach. An interesting point to note is that when comparing adopter households with non-adopters, it is seen that adopters did better than their counterfactuals in reducing deprivations and, hence improving welfare.

Table 8: Impact of technology adoption on Multidimensional Deprivation (overall)

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNM	0.5885	0.6129	-0.026(-2.27)**
RM	0.5885	0.6257	-0.030(-4.20)***
KMa[10]	0.5885	0.6096	-0.021(-2.64)***
KMb[11]	0.5885	0.6102	-0.020(-2.48)**

Note: Statistically significant at the 1 percent (***) and 5 percent (**) probability levels respectively. T-statistics in parenthesis. Source: Author's computations using WB LSMS data (2015), (2018).

[9] In contrast to some previous studies like Alkire and Santos (2010) and Alkire and Foster (2011), this study does not censor the MPI deprivation scores to zero for those households with a deprivation less than 0.3 to preserve our sample size and data variability.

[10] Kernel-based matching with a band width of 0.06 and common support.

[11] Kernel-based matching with a band width of 0.03 and common support.

As discussed in the previous sections, one of the advantages of using the MPI approach for measuring poverty is that it can be disaggregated (decomposed) into its dimensions and indicators. Table 9 (in the Appendix) gives the results of the PSM estimation for the living standards dimension. The results show that adoption of the specified technology was associated with a drop of between 1.6-2.2 percent in living standards' deprivation and was statistically significant in all the matching methods. This is consistent with the overall (composite) MPI in terms of both sign and significance, but lower in magnitude in the case of living standards.

Table 10 gives the estimates of MPI's education dimension. In contrast to the overall and living standard deprivations, we observe that adoption of technology was not associated with a statistically significant change in education deprivation, except in the case of radius matching. This situation is repeated for the health dimension in Table 11 which shows results similar to those for education deprivation such that the association between the adoption and the degree of health deprivation is not statistically significant.

[Insert Table 9 about here]

[Insert Table 10 about here]

[Insert Table 11 about here]

Finally, we disaggregated the ATT term across regions using the SM method to see the region in which the impact was more significant and powerful (see Table 12 in the Appendix). What is interesting is that the most productive regions like Amhara and Oromiya registered a significant reduction in aggregate deprivation scores in all dimensions. This implies that adoption helped the treated group to reduce poverty in the two dominant regions in the range 5.4-7.1 percentage points in overall deprivation and 1.6-5.3 in each component of MPI. This is a large improvement in welfare for adopters as compared to the comparison group.

Similarly, regions such as Harari and Tigray also showed a reduction in deprivations due to technology adoption. The other striking result here is that the three most pastoral regions, Afar, Gambela, and Somalie, showed that an association between adoption and deprivations in all dimensions was not statistically significant. A possible reason for this is that agriculture in these regions is dominated by livestock production with less crop-based agriculture.

Overall, PSM's results support the existence of poverty-alleviation effects of technology adoption. However, this impact is not similar across different dimensions of poverty, with the living standards dimension driving the improvements in welfare. The impact on the education and health dimensions is not significant. A possible reason for this is the absence of a public awareness campaign and development of complementary infrastructure such as schools and health centers. Improvements in the components of living standards might not be channeled to education and health facility development.

[Insert Table 12 about here]

The other important disaggregation is based on the degree of deprivation. For ease of interpretation, we divided households into the least deprived if their deprivation score, C_i, was less than 0.3; moderately deprived (C_i between 0.3 and 0.5); and severely deprived, if C_i was greater than or equal to 0.5. Table 13 gives the impact of the technology on overall MPI for different ranges of the deprivation scores.

The first two columns of Table 13 present the results of deprived and non-deprived households respectively. The results in the first column suggest that the deprived households experienced a reduction in MPI of about 3.40 percentage points, while non-deprived households faced a reduction in poverty of only 0.5 percent, and it was not statistically significant. This indicates that the poverty reduction impact of technology was significant and more powerful among the deprived households. The last three columns show the severity of the deprived (or degree of severity). In the fourth column, we see that the severely deprived households reduced poverty at a higher rate. This shows a diminishing impact of technology on overall poverty levels.

Table 13: Degrees of Overall deprivation and ATT by Adoption Status

Adoption(1,0) and ATT	C_i (Deprivation Score) Ranges				
	$C_i \geq 0.3$	$C_i < 0.3$	$0.3 \leq C_i < 0.5$	$0.5 \leq C_i < 0.75$	$C_i \geq 0.75$
ATT	-0.034***	-0.005	-0.002	-0.010**	-0.004
Adopters	762	42	157	511	94
Non-Adopters	1,699	77	272	1,092	335
Total	2,461	119	429	1,603	429

Note: Statistically significant at the 1 percent (***) and 5 percent (**) probability levels respectively.

Source: Author's computations using WB LSMS data (2015), (2018).

There is one drawback of the PSM estimation, that it cannot provide consistent estimations of causal effects in the presence of a hidden bias. Thus, to check for the robustness of our PSM findings and to control for an unobservable selection bias we estimated ESR. Before estimating ESR, we checked whether the model was correctly identified or not in terms of the instruments used in the model. For the ESR model to be identified the issue of exclusion restrictions is an important criterion **(**Di Falco et al., 2011). We employed a simple falsification test following Di Falco et al. (2011) and Shiferaw et al. (2014) to test the validity of the instruments. We used the variables related to region-dummies (for example, Oromiya-Dummy and Harari-Dummy) as selection instruments in the outcome function and two other variables, crop rotation and access to credit services, after the falsification test (Table 14).

The idea behind performing a falsification test is, "if a variable is a valid selection instrument, it will affect the adoption decision in the selection equation but it will not affect the outcome variable (aggregate deprivation score) among farm households that did not adopt the technology" **(**Di Falco et al., 2011, p.7)**.** Table 14 in the Appendix shows that the variables Oromiya-Dummy, Harari-Dummy, crop rotation, and access to credit services can be considered as valid selection instruments as they are jointly statistically significant drivers of the decision to adopt or not adopt the technology under study as the bottom part of Table 14 shows (Model 1, $\chi 2 = 114.42$; $p = 0.00$) but not for the aggregate deprivation score of the farm households that did not adopt the technology (Model 2, F-stat. = 0.96, $p = 0.41$).

[Insert Table 14 about here]

The FIML estimates of the ESR model are reported in Table 15. The first column gives the estimated coefficients of selection Equation (4) on adopting the specified technology whereas the second and third columns give the aggregate deprivation score estimated using Equations (5a) and (5b) for the two farm household groups.[12]

The results of the endogenous switching regression model estimated by FIML show that the estimated coefficient of correlation between the adoption (selection) equation and the aggregate deprivation score (outcome) equation (ϕ_j) is statistically significant. The results also show that both observed and unobserved factors influenced the decision to adopt modern agricultural technologies and welfare outcomes given the adoption decision. The significance of the coefficient of correlation between the adoption equation and the welfare (aggregate deprivation score) of the adopters indicates that self-selection occurred in the adoption of improved agricultural technologies.

Table 15: Full information maximum likelihood estimates of the switching regression model: Dependent variables: Adoption (1/0) and aggregate deprivation score (c_i)

Variables	FIML Endogenous Switching Regression		
	Adoption (1/0)	Adoption =1 (adopters)	Adoption=0 (non-adopters)
Sex(male=1)	-0.017*0.16)	-0.073(3.34) ***	-0.044(3.59) ***
Age(years)	0.023(1.76) *	0.002(0.85)	0.003(1.93) *
Age^2(squared values of age)	-0.001(1.63) *	0.000(1.75) *	0.000(0.23)
Household size(AE)	0.064(1.71) *	-0.012(1.18)	-0.015(2.45) **
Household size square (AE^2)	-0.006(1.77) *	0.000(0.82)	0.001(2.21) *
Marital status(married=1)	0.067(0.60)	-0.018(0.79)	-0.027(2.11) *
Extension service(yes=1)	1.321(20.66) ***	-0.006(0.10)	-0.055(3.89) ***
Crop rotation(yes=1)	0.326(0.60)		
Credit service(yes=1)	0.221(3.06) ***		
Oromiya-dummy (Oromiya=1)	0.859(6.08) ***		
Harari-dummy (Harari=1)	1.200(6.53) ***		
Amhara-dummy (Amhara=1)	0.441(3.08) ***	-0.042(2.08) **	0.067(6.68) ***
Tigray-dummy (Tigray=1)	-0.122(0.76)	0.037(0.80)	0.040(3.04) ***
SNNP-dummy (SNNP=1)	1.274(9.59) ***	0.035(1.68) *	-0.031(2.92) ***
Constant	-3.045(8.48) ***	0.684(4.56) ***	0.571(14.69) ***
(ϕ_j)		0.154***	0.166***
LR test of indep. eqns: 3.26 *			

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively.

T-statistics in parenthesis. Source: Author's computations using WB LSMS data (2015), (2018).

The differences in the aggregate deprivation score's coefficients between farm households that adopted improved agricultural technologies and those that did not show the presence of heterogeneity in the sample households (see Table 15, Columns 2 and 3). For example, the two

[12] The 'movestay' command of Stata was used for estimating the endogenous switching regression model by FIML (Lokshin and Sajaia, 2004).

groups (adopters and non-adopters) differ in factors like household age, Tigray-Dummy, extension service, family size, and marital status as the aggregate deprivation score equation of ESR shows. The aggregate deprivation score function of farm households that adopted improved agricultural technologies is significantly different from the aggregate deprivation score of farm households that did not adopt the technology and the likelihood-ratio test for joint independence of the three equations is reported in the last line of Table 15 and this is statistically significant.

In Column 1, Table 15 the selection equation shows that the decision to adopt the specified technology was determined by all factors except marital status, Tigray-Dummy, crop rotation, and household head's sex. Household head's age square and household size square negatively affected the technology adoption decision while the remaining significant variables were positively associated.

The results in Table 16 also show that using both ESR and PSM methods showed that the impact of the technology was almost similar such that it led to a reduction in the aggregate level of deprivation scores and the results were statistically significant. The findings also show that farm households that did not adopt the technology would have benefited significantly had they adopted it as indicated in the ESR results (ATU).

Table 16: Endogenous switching regression model, expected conditional and average treatment effects of adoption on c_i and a comparison with PSM's results

Estimation types	Decision		Adoption effect
	Adopters	Non-adopters	
ESR			
Farm households that did adopt (ATT)	(a) 0.589	(c) 0.603	-0.014(5.24) ***
Farm households that did not adopt (ATU)	(d) 0.596	(b) 0.626	-0.030(13.53) ***
Heterogeneity effect (HE)	BH_1[13] = -0.007	BH_1[14] = -0.023	TH[15] = 0.016
PSM			
NNM	0.589	0.613	-0.024(-2.27)**
RM	0.589	0.626	-0.037(-4.20)***
KMa	0.589	0.610	-0.021(-2.64)***
KMb	0.589	0.610	-0.020(-2.48)**

Note: Statistically significant at the 1 percent (***) and 5 percent (**) probability levels respectively.
T-statistics in parenthesis.
Source: Author's computations using WB LSMS data (2015), (2018).

[13] The effect of base heterogeneity for adopters (a–d).
[14] The effect of base heterogeneity for non-adopters (c–b).
[15] Transitional heterogeneity (ATT-ATU).

5. CONCLUSION

The objective of this study was examining the impact of adopting improved agricultural technologies on multidimensional poverty status of rural households in Ethiopia. The study used the PSM and ESR methods in combination with the Alkire and Foster (2007, 2011a) counting approach for measuring MPI. The data used in the empirical part is from the World Bank's LSMS, Wave 3 (2015).

The study connected the multidimensional poverty methodology to the impact evaluation technique in the agriculture sector. In addition, the Alkire and Foster methodology (2007, 2011a) allowed us to decompose the poverty measure into its deprivation components, indicators, and other household or spatial level characteristics.

In the unidimensional approach, the study used consumption expenditure and the results of the poverty analysis showed that about 42 percent of the households were poor in the country. Using the relative poverty line, the median value of consumption expenditure, about 47 percent of the households were below the poverty line. Concerning the adoption status of households, adopters of technology were slightly better-off than non-adopters implying that modern technologies improved adopters' welfare. A comparison between sexes of household heads indicated that female headed households were less impoverished as compared to male headed households. A region-wise comparison showed that Benishangul was the most impoverished region (59.8 percent) followed by SNNP (57.1 percent). On the other hand, in the Dire Dawa region the incidence of poverty was the lowest (3.30 percent) followed by the Harari region (14.2 percent). The empirical results also showed that average welfare (per capita consumption expenditure) gains of adopted technology ranged from Birr 152 to Birr 203 while the reduction in poverty ranged between 0.20 - 0.31 percentage points.

The study also discussed the measurement of the multidimensionality of poverty. The results showed that people were the most deprived in the education dimension (41.8 percent) followed by the standard of living dimension (34.6 percent). Indicator-wise, people were the most deprived in terms of years of schooling (24.6 percent) while they were less deprived in access to clean water (3.2 percent). PSM's results showed that the adoption of technology reduced the overall deprivation in the range 2.0-3.0 percent. The living standards component of MPI drove the change indicating a reduction in living standards' deprivation between 1.6-2.2 percent. Regionally a high reduction in deprivation was observed in Amhara region (7.1 percent) followed by Oromiya region (5.3 percent). The results also showed that the impact was significantly higher in the severely deprived households (whose deprivation score was greater than 0.50). Deprived households experienced a reduction in MPI of about 3.40 percent, while non-deprived households had a reduction in poverty by only 0.5 percent. This shows that the poverty reduction impact of technology was significant and higher among the deprived households. We also used the ESR technique to control for unobserved heterogeneity of household characteristics and the results were almost similar to those of the PSM approach. Finally, we noted that the inclusion of additional dimensions of poverty improved our measurement of poverty.

6. POLICY IMPLICATIONS

The results of this study show that the extent of multidimensional poverty is very high, and the impact of technology varies across regions and by sex which requires concerted policy interventions. There are large regional variations. Policymakers should consider regional variations, community realities, and households' characteristics for fighting poverty. Expanding education and production opportunities such as access to credit, improved seeds, and information are important policy interventions that will help reduce the households' poverty status.

Though the level of income poverty seems lower, multidimensional poverty still remains high which requires government interventions. This requires a revision of national poverty reduction strategies to incorporate the multidimensional aspects of deprivation and combating a range of features of poverty. It is also important to consider appropriate agricultural technologies that most affect multidimensional poverty and its components. Future poverty alleviation policies and strategies should view poverty broadly and design appropriate multifaceted interventions.

REFERENCES

Adekambi, S. A., Diagne, A., Simtowe, F., & Biaou, G. (2009). The Impact of Agricultural Technology Adoption on Poverty: The Case of, NERICA Rice Varieties in Benin. Contributed paper prepared for presentation at the International Association of Agricultural Economists' conference, Beijing, China, August 16-22, 2009.

Alkire, S. (2011). Multidimensional Poverty and its Discontents. OPHI Working Paper 46, Oxford Poverty and Human Development Initiative, *University of Oxford.*

Alkire, S., & Foster, J. (2011a). Counting and Multidimensional Poverty Measurement. *Journal of Public Economics*, 95(7–8), 476–487.

Alkire, S., & Foster, J. (2011b). Understandings and Misunderstandings of Multidimensional Poverty Measurement. *Journal of Economic Inequality*, 9(2), 289–314.

Alkire, S., & Foster, J. (2016). Dimensional and Distributional Contributions to Multidimensional Poverty. OPHI Working Paper 100, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., & Foster, J. E. (2007). Counting and Multidimensional Poverty Measurement. OPHI Working Paper 7. *University of Oxford*.

Alkire, S., & Foster, J. E. (2009). Counting and multidimensional poverty measurement (OPHI Working Paper No. 32).

Alkire, S., & Santos, M.E. (2010). Acute multidimensional poverty: A new index for developing countries, OPHI Working Paper No. 38, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., & Santos, M.E. (2013). A Multidimensional Approach: Poverty Measurement and Beyond. *Social Indicators Research*, 112(2), 239-257.

Alkire, S., & Santos, M.E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development* 59, 251–274.

Alkire, S., & Sarwar, M.B. (2009). Multidimensional Measures of Poverty and Well-being. Working Paper. Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Roche, J. M., Ballon, P., Foster, J., Santos, M. E., & Seth, S. (2015). *Multidimensional Poverty Measurement and Analysis*. Oxford: Oxford University Press, USA.

Asfaw, S., & Shiferaw, B. (2010). Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Poster presented at the 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19 – 23, 2010

Asfaw, S., Kassie, M., Simtowe, F., & Leslie, L. (2012). Poverty Reduction Effects of Agricultural Technology: A Micro-evidence from Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Asfaw, S., Shiferaw, B., & Simtowe, F. (2010). Does technology adoption promote commercialization? Evidence from chickpea technologies in Ethiopia. In *CSAE 2010 conference on Economic Development in Africa, University of Oxford, UK*.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295.

Atkinson, A.B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality*, *1*(1), 51–65.

Bataan, Y. M. (2008). Multidimensional Measurement of Poverty in Sub-Saharan Africa. OPHI Working Paper 13, Oxford University, August 2008.

Battiston, D., Cruces, G., Lopez-Calva, L. F., Lugo, M. A., & Santos, M. E. (2013). Income and Beyond: Multidimensional Poverty in six Latin American countries. *OPHI Working Paper 17, Oxford Poverty and Human Development Initiative,* University of Oxford.

Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: a propensity scores matching approach. *World Development, 38*(7), 1024-1035.

Bourguignon, F., & Chakravarty, S.R. (2003). The Measurement of Multidimensional Poverty. *Journal of Economic Inequality*, 1, 25–49.

Carter, D. W., & Milon, J. W. (2005). Price knowledge in household demand for utility services. *Land Economics*, *81*(2), 265-283.

Di Falco, S., Veronesi, M., & Yesuf, M., (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93 (3), 829–846.

Faltermeier, L., & Abdulai, A. (2006). The Adoption of Water Conservation and Intensification Technologies and Farm Income: A Propensity Score Analysis for Rice Farmers in Northern Ghana, Annual Meeting, July 27-29, Orlando, Florida, American Agricultural Economics Association.

Ferede, S., Ayele, G., & Teklewold, H. (2003). Impact of Technology on Households Food Security, in Tef and Wheat Farming Systems of Moretna_Jiruworeda. Ethiopian Agricultural Research Organization (EARO), Research Report No.48.

Foster, J., Greer, J., & Thorbecke, E. (1984). A Class of Decomposable Poverty Measures. *Econometrica*, 52(3), 761-766.

Hundie, B., & Admassie, A. (2016). "Potential Impacts of Yield-Increasing Crop Technologies on Productivity and Poverty in two Districts of Ethiopia", in F. Gatzweiler and J. von Braun (eds), *Technological and Institutional Innovations for Marginalized Smallholders in Agricultural Development.* Springer International Publishing (pp. 397-421).

Just, R. E., & Zilberman, D. (1983). Stochastic structure, farm size and technology adoption in developing agriculture. *Oxford Economic Papers*, *35*(2), 307-328.

Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda. *Environment for Development Discussion Paper-Resources for the Future (RFF)*, (10-11).

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World development*, *39*(10), 1784-1795.

Kelsey, J. (2011). Market inefficiencies and the adoption of agricultural technologies in developing countries. Center for International Development at Harvard University, and Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley).

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, 66, 695–706.

Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, *4*(3), 282-289.

Maasoumi, E., & Xu, T. (2015). Weights and substitution degree in multidimensional well-being in China. *Journal of Economic Studies*, 42(1), 4–19.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics* (No. 330.028 M179). Cambridge University Press.

Martinetti, E.C (2000). A multi-dimensional assessment of well-being based on Sen's functioning theory. *Rivista internazionale di scienze sociali*, 108(2), 207-239.

Mendola, M. (2003). Agricultural technology and poverty reduction: A micro-level analysis of causal effects. *Centro Studi Luca D'Agliano Development Studies Working Paper*, (179), November, University of Milan-Bicocca, Italy.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy*, *32*(3), 372–393.

MoFEC (Ministry of Finance and Economic Cooperation) (2017). *Ethiopia's Progress towards Eradicating PovertyŁ an Interim Report on 2015/16 Poverty Analysis Study.* Addis Ababa: National Planning Commission.

MoFED (Ministry of Finance and Economic Development) (2012). *Ethiopia's progress towards eradicating poverty: An interim report on poverty analysis study (2012/13).* Addis Ababa: The Federal Democratic Republic of Ethiopia.

Mulugeta, T., & Hundie, B. (2012). Impacts of Adoption of Improved Wheat Technologies on Households' Food Consumption in Southeastern Ethiopia. Selected Poster prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, August 18-24, 2012.

Rahm, M. R., & Huffman, W.E. (1984). The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. *American Journal of Agricultural Economics*, 66 (4), 405–413.

Ravallion, M., Chen, S., & Sangraula, P. (2007). New evidence on the urbanization of global poverty. *Population and Development Review*, *33*(4), 667-701.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica*, *70*(1), 41-55.

Sahu, S. K., & Das, S. (2016). Impact of agricultural related technology adoption on poverty: A study of select households in Rural India. In *Technology* (pp. 141-156). Springer, Singapore.

Sanchez, P. A., Denning, G. L., & Nziguheba, G. (2009). The African green revolution moves forward. *Food Security*, *1*(1), 37-44.

Sen, A. (1976). Poverty. An Ordinal Approach to Measurement. *Econometrica*, 44, 219–231.

Sen, A. (1979). Personal Utilities and Public Judgments: Or what's wrong with Welfare Economics. *The Economic Journal*, 89, 537–558.

Sen, A. (1985). *Commodities and Capabilities.* Amsterdam: North-Holland.

Sen, A. (1987). *The Standard of Living*. Cambridge: Cambridge University Press.

Sen, A. (1992). *Inequality Reexamined*. Cambridge: Harvard University Press.

Sen, A. (1995). The political economy of targeting public spending and the poor: Theory and evidence. Baltimore: Johns Hopkins University Press.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272-284.

Tesfaye, S., Bedada, B., & Mesay, Y. (2016). Impact of improved wheat technology adoption on productivity and income in Ethiopia. *African Crop Science Journal*, *24*(1), 127-135.

The World Bank (2008). *World development report 2008*: *agriculture for development.* Washington, DC: The World Bank.

Tsui, K. Y. (2002). Multidimensional Poverty Indices. *Social Choice and Welfare,* 19(1), 69–93.

Wu, H., Ding, S., Pandey, S., & Tao, D. (2010). Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching analysis in rural China. *Asian Economic Journal*, *24*(2), 141-160.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2015). Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics*, *46*(4), 515-526.

APPENDIX

Table 2: Absolute and Relative poverty status by different categories

By Adoption Status and Gender					
Headcount Ration (P_o)					
Adoption status			Sex		
Adopter	Non-Adopter	Total	Male	Female	Total
0.416	0.421	0.420	0.423	0.401	0.420
Relative Poverty (percent)					
Adoption status			Sex		
Adopter	Non-Adopter	Total	Male	Female	Total
0.468	0.483	0.472	0.482	0.437	0.472

By Region

Region	Headcount Ratio(P_o)	Relative Poverty (percent)[16]	M_o
Afar	0.429	0.407	0.658
Amhara	0.495	0.577	0.637
Benishan	0.598	0.646	0.511
Dire Daw	0.033	0.124	0.563
Gambella	0.472	0.467	0.556
Harari	0.142	0.156	0.536
Oromiya	0.331	0.388	0.576
Somalie	0.222	0.300	0.662
Tigray	0.332	0.433	0.576
SNNP	0.571	0.560	0.567
Total	0.420	0.472	0.586

Source: Author's computations using WB LSMS data (2015), (2018).

[16] The median of consumption expenditure is used for constructing a relative poverty line. More people become poor under the relative poverty line because the absolute poverty line constructed by MoFED is lower (3,781 Birr) as compared to the median value of consumption expenditure (4,569.54 Birr). We cannot use MoFEC's absolute poverty line developed in 2016 as it is inflated.

Table 3: Covariate Balance Indicators before and after Matching: Quality Test

Outcome Variable	Matching type	Pseudo R^2 Before matching	Pseudo R^2 After matching	LR χ 2 (p − value) Before matching	LR χ 2 (p − value) After matching	Mean standardized bias before matching	Mean standardized bias After matching
TDS[17]	NNM	0.195	0.001	663.22	2.12	37.8	2.3
	RM	0.195	0.007	663.22	16.97	35.2	4.2
	KM	0.195	0.004	663.22	8.63	35.9	2.5
LSDS[18]	NNM	0.204	0.002	693.15	3.65	48.8	2.0
	RM	0.204	0.001	693.15	3.64	48.8	2.4
	KM	0.204	0.002	693.15	5.78	48.8	3.4

Source: Author's computations using WB LSMS data (2015), (2018).

Table 9: Impact of technology adoption on Living Standard Deprivation

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNM	0.2504	0.2665	-0.016(-2.45)**
RM	0.2504	0.2729	-0.022(-5.59)***
KMa[19]	0.2504	0.2694	-0.020(-4.29)***
KMb[20]	0.2504	0.2675	-0.019(-4.74)***

Note: Statistically significant at the 1 percent (***) and 5 percent (**) probability levels respectively. T-statistics in parenthesis.
Source: Author's computations using WB LSMS data (2015), (2018).

Table 10: Impact of technology adoption on Education Deprivation

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNM	0.4008	0.4058	-0.005(-0.62)
RM	0.4008	0.4175	-0.010(-1.84)*
KMa	0.4008	0.4026	-0.002(-0.43)
KMb	0.4008	0.4036	-0.001(-0.22)

Note: Statistically significant at the 10 percent (*) probability level. T-statistics in parenthesis.
Source: Author's computations using WB LSMS data (2015), (2018).

[17] Total deprivation score.
[18] Living standards deprivation score.
[19] Kernel-based matching with a band width of 0.06 and common support.
[20] Kernel-based matching with a band width of 0.03 and common support.

Table 11: Impact of technology adoption on Health Deprivation

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNM	0.1361	0.1393	-0.003(-0.45)
RM	0.1361	0.1428	-0.005(-1.17)
KMa	0.1361	0.1365	-0.001(-0.43)
KMb	0.1361	0.1395	-0.001(-0.02)

Note: T-statistics in parenthesis.

Source: Author's computations using WB LSMS data (2015), (2018).

Table 12: ATT Decomposition by Regions

Region	ATT			
	Overall	Education	Health	Standard of Living
Afar	0.00	0.00	0.00	0.00
Amhara	-0.071***	-0.004	-0.053***	-0.028**
Benishangul	0.006	-0.003	0.019	-0.011
Dire Daw	0.00	0.00	0.00	0.00
Gambella	0.00	0.00	0.00	0.00
Harari	-0.053*	-0.081***	0.050**	-0.039**
Oromiya	-0.054***	-0.034**	-0.016*	-0.017**
Somalie	0.00	0.00	0.00	0.00
Tigray	-0.030*	0.013	0.005	-0.028*
SNNP	0.009	0.003	-0.002	-0.001
Total	-0.030***	-0.012**	-0.012**	-0.015***

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively.

Source: Author's computations using WB LSMS data (2015), (2018).

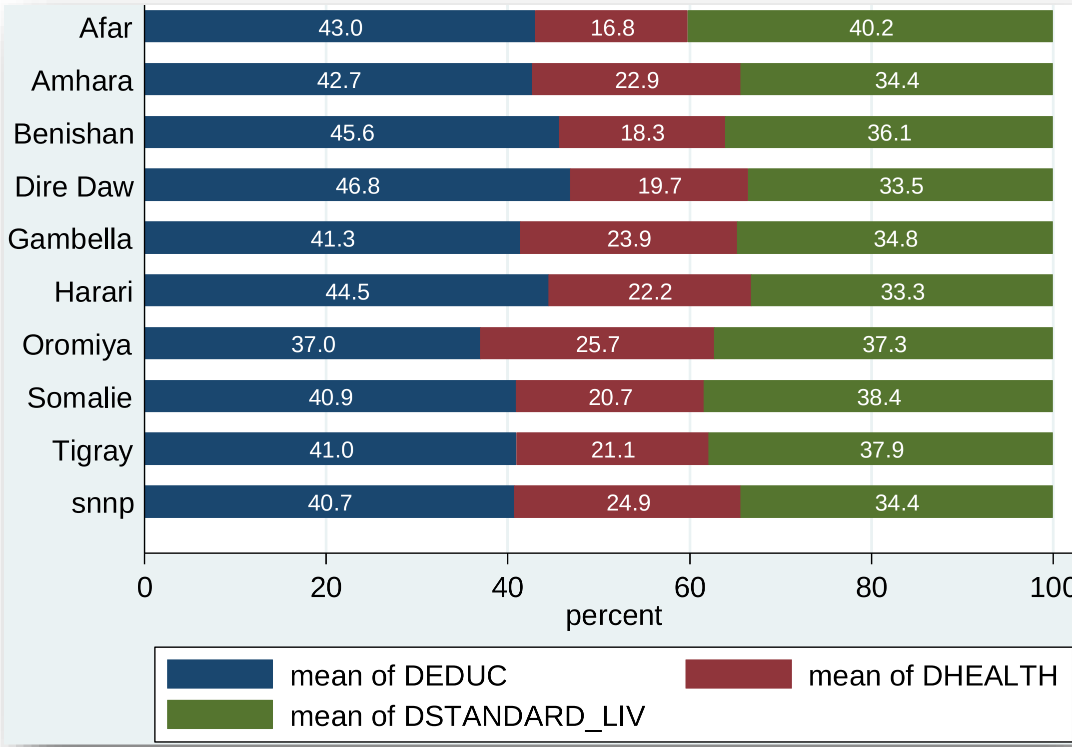

Figure 2: Status of each of the 10 regions in MPI scores and contribution of each component to the deprivation score

Table 14: Falsification Test – Test on The Validity of The Selection Instruments

Variables	Model 1	Model 2
	Adoption (1/0)	c_i of Non-Adopters
Oromiya-Dummy	0.213***(0.061)	-0.002(0.011)
Harari-Dummy	0.966***(0.131)	-0.033(0.020)
Crop rotation	0.641***(0.067)	0.005(0.009)
Credit service	0.486(0.634)	-0.028**(0.012)
Constant	-1.174***(0.062)	0.628***(0.008)
Wald test	$\chi 2$ = 114.42***(p=0.000)	F-stat. = 0.960(p=0.41)
N	2, 752	1,980

Note: Statistically significant at the 1 percent (***) and 5 percent (**) probability levels respectively. Robust standard errors in parentheses

Source: Author's calculations using WB LSMS data (2018).

Paper 3: Do Improved Agricultural Technologies Affect Household Food Security and Child Nutrition? The Case of Rural Ethiopia

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Abstract

New agricultural technologies and improved practices play a key role in increasing agricultural production and productivity thus improving national food security in developing countries. A large body of empirical literature shows that adoption of agricultural technologies can affect households' welfare indicators like poverty, food security, productivity, employment, and income both directly and indirectly. However, existing studies are largely cross-sectional in nature. At the same time, they are also based on similar datasets and focus on very limited aspects of agricultural technologies. This study uses a panel data analysis using fixed effects combined with the propensity score matching and the endogenous treatment effects techniques. The objective of this study is assessing the impact of improved agricultural technology adoption on household food security and child nutrition in rural parts of Ethiopia. This study explores and links adoption-nutrition to which most previous studies have paid little attention. The estimation results on the first two outcome variables, consumption expenditure and child nutrition, show that adopting improved agricultural technologies has a robust, significant, and positive impact on per capita consumption expenditure and child nutrition. Concerning the remaining two outcome variables, food shortages and whether a household worries about the availability of food or not, there is no strong support for the impact of improved agricultural technologies on them.

Keywords: Food security; nutrition; technology adoption; Ethiopia
JEL Classification Codes: D13; I12; I30; O33; Q10

1. Introduction

1.1 Background

"Ensuring a stable and healthful food supply for the world's growing population has become increasingly urgent, particularly in the face of climate change. Despite expected increases in food production in developing countries, the number of people at risk of hunger is predicted to grow, especially in the world's poorest regions, such as sub-Saharan Africa. ..."

.... Weisenfeld and Wetterberg (2015, p.1)

The diffusion and utilization of improved agricultural technologies and supervision of improved practices can be traced back thousands of years to different parts of the globe including in China, Mesopotamia, Egypt, and the Americas. The origins of public or government financed extension and advisory services can be traced back to Ireland and the United Kingdom during the middle of the 19th century. At the time of the potato famine in Ireland (1845–1851), agricultural advisors effectively supported Irish potato producers in diversifying into different agricultural outputs (Swanson and Rajalahti, 2010).

Evidence shows that improved agricultural technologies are essential for improving small-scale farmers' household food security, raising rural incomes, and creating national surpluses that can provide the basis for economic growth thereby leading to improvements in social welfare. Yet, globally the adoption of agricultural technologies has been uneven and uncertain for many decades. For example, the adoption of new and improved agricultural technologies such as high yielding varieties (HYVs) led to the green revolution in Asia. But Africa has lagged way behind the rest of the world in agricultural production and productivity, perhaps due to low development and lesser uptake of new and improved agricultural technologies such as HYVs, chemical fertilizers, pesticides, and other improved practices.

Adoption of new agricultural technologies and improved practices play an enormous role in increasing agricultural production and hence improving national food security in developing countries. If the application of these new technologies is successful, it could stimulate overall economic growth through inter-sectoral linkages while conserving natural resources (Faltermeier and Abdulai, 2006; Sanchez et al., 2009).

Some studies on food security (for example, Weisenfeld and Wetterberg, 2015) argue that technological innovations and improved farming practices exist that increase agricultural production and productivity while also enhancing climate resilience. These include drought tolerant seed varieties, drip irrigation, and the precise application of fertilizers and agro-chemicals, as well as practices such as integrated pest management, conservation farming, and improved watershed and soil management. Even though this is the case, getting these technologies into the hands of the farmers who will benefit the most from them is not a simple task. Although technology is not the end goal of improving social welfare, it is a means of addressing the food production side of the food security equation. Increasing food production simply by using more land, water, seeds, fertilizers, and pesticides will not achieve the significant improvements in productivity that are necessary for advancing the economic well-being of the food insecure.

Several empirical studies (Amare et al., 2012; Asfaw et al., 2012b; Becerril and Abdulahi,2010; Hundie and Admassie, 2016; Kassie et al., 2011; Moyo et al., 2007) argue that adoption of agricultural technologies can affect households' welfare indicators like poverty, food security, productivity, employment, and income both directly and indirectly. This vast literature shows that the direct effects of improved technologies include productivity gains and low cost of production which can further improve the adopters' incomes while the indirect benefits of technology adoption may come in the form of increased supply which may lower food prices. Increased productivity gains may also encourage demand for labor which may translate into increased employment and earnings for the poor who usually supply their labor for activities in the agriculture sector. In addition to improving productivity, technology adoption can also reduce per unit cost of production, increase food supply, and raise incomes of adopting producers. Adoption of improved technologies has been identified as a key measure for achieving food security. Peasant farmers have the potential to enhance their welfare as well as their food security situation if they make use of improved agricultural technologies (Asfaw et al., 2012a; Feleke and Zegeye, 2006; Langyintuo et al., 2008) and reduce their poverty levels (Mendola, 2007; Wu et al., 2010). It can also improve nutritional status (Kumar and Quisumbing, 2011) and reduce the risks of crop failures (Hagos et al., 2012).

As some previous studies (for example, Asfaw et al., 2012b) show that , in much of sub-Saharan Africa (SSA), the agriculture sector is a fundamental source of economic growth, overcoming poverty, and improving achievements in food security though the sector in the region is often characterized by low use of modern technologies and lower productivity. Improving the productivity, profitability, and sustainability of smallholder farming is therefore the main pathway out of poverty for these countries (Muzari et al., 2012; Odame et al., 2013; Ogada et al., 2014; The World Bank, 2008; Yu et al., 2011).

Therefore, technological changes in African agriculture are a basic factor for achieving a sustained increase in food production and overall economic growth. The special nutrition problems in Africa relate not only to factors like low levels of food availability and absence of relevant technology but also to seasonality and to the high variability of food intake across periods (Braun, 1988). Adopting agricultural technologies also leads to more stability in food availability and consumption, which in turn improves children and women’s nutritional status. Zeng et al. (2014) also state that incremental household calories improve the nutritional status of children in particular. Similarly, adopting improved technologies also has a positive overall impact on child nutrition.

Evidence shows that in the East African countries Ethiopia is one of the poorest in the region and that nearly 30 percent of the households in the country are in extreme poverty and hunger which has remained consistent over many years (The World Bank, 2015). Over 30 percent of the population in the country is undernourished and faces problems related to prevalence of food inadequacy are 41.3 percent (FAO, 2015); 36 percent of the farming households in the country are engaged in subsistence farming and living on less than $2 per day. Therefore, improving agricultural production and productivity in the country is not a matter of choice but a necessity.

In Ethiopia, the agriculture sector is mainly characterized by smallholder farming where production activities are dominated by subsistence farming and productivity is very low, even less than the average production of sub-Saharan countries. On the other hand, there is a rapidly growing population, leading to an increasing gap between food production and consumption requirements. Agricultural output can be increased through expansion of the farmland under cultivation and/or by applying more inputs and technologies for production. The former approach is not a feasible strategy for increasing agricultural production in most of the food insecure countries where high population pressure is a limiting factor in increasing the area under cultivation.

Hence, intensification which entails investments in modern inputs and technologies is an appropriate option for attaining sustainable agricultural growth and increasing production in the sector. This can enhance agricultural productivity by improving farm resource utilization's efficiency based on the existing technologies and/or employing new agricultural technologies, which may lead to changes in the production frontier, increase output, and reduce food insecurity due to availability and consumption effects.

1.2 Rationale and Motivation

Technology adoption has been studied at the firm or household, the industry, and national levels. Some studies focus on how adoption spreads and investigate factors behind the diffusion of technology. Other studies examine basic characteristics of technologies that tend to be adopted quickly, while others focus on decision makers or firms' characteristics that relate to cases of early adoption. The scope, approach, and methods employed by these studies vary widely, though they all generate conflicting or/and inconclusive results; however, some common tendencies have also emerged from these studies (Rubas, 2004).

An analysis of literature suggests that there is evidence of increased work on the adoption of improved agricultural technologies and how this influences household welfare. However, these studies are largely cross-sectional and are based on similar datasets and focus on very limited aspects of agricultural technologies. Since most of the studies in this field of research are based on cross-sectional analyses and mostly use a single method of estimation, there are doubts about the reliability of their results. Several of these studies focus on limited aspects of technology which may suffer from inefficient parameter estimates, leading to inaccurate inferences of the model's parameters since it disregards cross-period correlations. Most previous studies use a single agricultural technology and do not compare multiple impacts of different technologies or improved practices; thus, this is a novel contribution of my study. In addition to these problems, it is difficult to control the impact of omitted variables leading to biased or unreliable estimates which most impact evaluation studies suffer from.

There are several studies on adopting agricultural technologies in Ethiopia. However, an additional side that we need to consider is that since adoption of technologies is a dynamic phenomenon, it is important to update the information based on currently available technologies being adopted by farmer households. Moreover, a specific association between the impact of adopting a technology on household welfare, the constraints of adopting a technology, and the type of technology adopted has not received adequate attention. Finally, specific causal linkages between agricultural technology adoption and child nutrition outcomes are rarely explored in existing impact evaluation literature. Thus, to fill this methodological and knowledge gap related to improved agricultural technologies, this study used databases obtained from two rounds of the World Bank's Living Standard Measurement Survey (LSMS) (2013 and 2015), that covers the whole of Ethiopia.

The main objective of this study is assessing the impact of improved agricultural technology adoption on household food security and child nutrition in the rural parts of the country. It also explores adoption-nutrition links while most studies focus on income generation and poverty reduction, rarely exploring nutritional improvements, particularly in children.

The rest of the study is organized as follows. Section 2 discusses selected works in the area of technology adoption while Section 3 assesses some of the common empirical challenges and estimation strategies in the impact evaluation process. Section 4 describes the methodology used for estimating the impact of the stated technology. The last three sections give the findings, concluding remarks, and some policy implications of the study's results respectively.

2. Literature Review

Adoption of an innovation within a social system happens through its adoption by individuals or groups. According to Feder et al. (1985), adoption is defined as the integration of an innovation in farmers' normal farming activities over an extended period. It is also noted that adopting an innovation is not permanent behavior and is instead characterized by a preference and decision over time by agents based on several factors. This implies that an individual may decide to discontinue the use of an innovation for a variety of personal, institutional, technical, or social reasons one of which might be the availability of another practice that is better in satisfying his/her needs and expectations.

Numerous studies have been conducted in the area of agricultural technology adoption and its related impact on welfare. A number of these studies evaluate the connection between causes and impacts using different estimation techniques.

Several studies in Africa show that adoption of improved agricultural technologies, though variably and incompletely assessed, had a significant impact on welfare indicators such as income, food security, and poverty reduction (for example, Adekambi, et al., 2009; Asfaw et al., 2010, 2012; Hundie and Admassie, 2016; Kassie et al., 2010; Shiferaw et al., 2014; Wanyama et al., 2010).

Asfaw et al. (2012) investigated the adoption and impact of modern agricultural technologies on smallholder welfare in Tanzania and Ethiopia, and their results showed that adopting the technologies had a robust, positive, and significant impact on per capita consumption expenditure and a negative effect on poverty reduction. Similarly, Shiferaw et al. (2014), studied adopting improved wheat varieties and their impact on household food security in Ethiopia. Their study showed that adoption of improved wheat varieties increased average per capita consumption expenditure of the sample households in general. From their findings, we see that the impact of the technology ranged between 209 and 260 Ethiopian Birr in terms of increase in average per capita consumption expenditure and an increase in the probability of food security in the range of 2.5–8.6 percent while significantly reducing the probability of chronic food insecurity from 1.3 to 3.0 percentage points. Transitory food insecurity also reduced in the range of 1.3–5.9 percent as a result of adopting improved wheat varieties in the country.

Khonje et al. (2015) assessed the impact of improved cassava varieties in Zambia and the results of different treatment effect estimators. Their assessment showed that adoption of improved cassava varieties led to significant gains in crop yields, household incomes, and food security. Using the number of months that the grains stayed in a store as a proxy for food security, Wanyama et al. (2005) showed that soil management technologies had a positive impact on the food security of the farming community within the soil management project area and its neighborhood in Kenya.

Ferede et al. (2003) assessed the impact of improved technology adoption on households' food security in teff and wheat growing areas in Ethiopia. Their study found that adopting improved agricultural technologies had a positive and significant effect on households' food security. Asfaw et al. (2010) examined the impact of adopting improved chickpea varieties on the level of commercialization of smallholder farmer households in Ethiopia. Their findings showed that adopting improved chickpea varieties had a positive and robust effect on the marketed surplus which reduced food insecurity of the adopter households under considerations.

Adekambi et al. (2009) investigated the impact of agricultural technology adoption of new rice varieties (NERICA varieties) on poverty in Benin. Their results showed that adopting NERICA varieties led to increased productivity for rice farmers. Kassie et al. (2010) found that improved ground technologies had a significant positive impact on crop yields and poverty reduction in Uganda. Simon (2013) assessed the role of agricultural technologies in improving rural households' welfare in Zimbabwe. Their results showed that households that adopted new technologies had high consumption expenditures and agricultural incomes implying that technology adoption improved household welfare.

Asfaw et al. (2012b) and Amare et al.'s (2012) studies in Tanzania on the impact of improved agricultural technologies found that the adoption of improved technologies such as pigeon pea and maize varieties increased household welfare through consumption expenditure.

Other studies elsewhere with similar objectives under different conditions also confirm that adoption of improved agricultural technologies and practices led to significant improvements in farmers' welfare. These improvements were in the form of an increase in crop output and incomes, improved market surplus and lower food prices, improved food security, and reduced poverty status of farm households.

Studies conducted in Asia also show similar positive and significant impacts of improved agricultural technologies on welfare. In a micro-level analysis, Mendola (2003) evaluated the causal effects of agricultural technology on poverty reduction. The findings showed that adopting agricultural technology had a robust and positive effect on farm households' well-being. The author also conducted related work using a propensity score matching method. Mendola (2007), examined the impact of agricultural technology adoption on poverty reduction in rural Bangladesh. The results showed that adopting the specified technology had a robust and positive impact on farm households' well-being. The findings also showed that the average income differences between adopters and non-adopters were almost 30 percent higher for the treated groups.

Wu et al. (2010) assessed the impact of agricultural technology adoption on farmers' well-being in rural China and their findings showed that adopting agricultural technologies had a positive impact on farmers' well-being thereby improving household incomes. Sahu and Das (2016) used cross-sectional household level data in India collected in 2014 to evaluate the impact of adopting agricultural related technologies. Their findings showed that there were robust, positive, and significant impacts of technology on per capita consumption expenditure and negative impacts on poverty reduction.

Woog (2008) studied the potential impact of advanced maize genomic technology on corn cultivation in northern China. The study confirmed that there existed numerous potential advantages which can be associated with the introduction of advanced maize seed varieties including reduced crop losses and increased yields. Apart from these important effects, the adoption of high-oil content corn in the area benefited small scale farmers through higher prices for the quantity produced.

Hossain (2009) researched the impact of adopting modern rice varieties (MVs) on food security in Bangladesh. Besides attaining higher food security, he also identified several other impacts of these modern rice varieties. His findings showed that an increase in yields by adopting MVs was much higher than an increase in adoption costs. Cost per unit of output went down with increased production of MVs. Following the adoption of MVs, the unit cost of production was 22 percent lower in the area where they were cultivated.

Apart from Africa and Asia, some studies have also been done elsewhere to assess the impact of agriculture related improved technologies and practices. For example, Becerril and Abdulai (2010) in their study in Mexico used PSM to analyze the impact of adopting improved maize varieties on household incomes and poverty reduction. They found that this adoption had a positive and significant impact on farm households' welfare measured by per capita consumption expenditure and had a negative impact on poverty reduction. In this regard, the adoption of improved maize varieties helped in raising the household per capita consumption expenditure by an average of 136-173 Mexican Pesos and it reduced the probability of falling below the poverty line by about 19-31 percent in general.

Bond et al. (2005) studied the economic and environmental impacts of adopting genetically modified rice (GMr) varieties in California. Their findings showed that a production strategy which included GM rice varieties could lead to significant economic benefits for many growers in at least the near term. Those most likely to benefit from the adoption of transgenic rice varieties were growers with relatively high herbicide material and application costs.

Using an instrumental variable model, Salazar et al. (2015) evaluated the impact of agricultural technology adoption on small subsistence farmers' food security and productivity in Bolivia. Their results showed that participation in the improved practice program in the agriculture sector helped the adopters of the technology in increasing agricultural productivity, household incomes, and improved food security status in Bolivia.

Coming to the impact of agricultural technologies and improved practices on nutrition, much less is known about their welfare impact and relatively less research has been conducted on this aspect. Tigabu and Gebeyehu (2018) investigated the role of agricultural extension services and technology adoption in food and nutrition security in Ethiopia. Their findings showed that if farmer households adopted technologies once then they were more likely to adopt the technologies again implying that technology made adopters better-off in welfare status as compared to other comparable groups. Their results also showed that agricultural extension services and technology adoption had a significant and positive impact on the nutrition status of households in Ethiopia.

Zeng et al. (2014) assessed the impact of improved maize varieties on child nutrition in Ethiopia by using household survey data from the rural parts of the country. Their estimation results showed that adopting improved maize varieties had a positive overall impact on child nutrition measured by height-for-age z-scores (HAZ) and weight-for-age z-scores (WAZ). The main channel through which the adoption of improved maize varieties affected child nutrition was through increasing consumption of own-produced maize.

Braun (1988) studied the effects of technological changes in agriculture on food consumption and nutrition in West Africa. His results showed that technological changes significantly improved children's nutritional status through increased incomes and then through increased food consumption measured by the intake of calories. He showed that much of the increased income was spent on increased calorie consumption thereby increasing children's nutritional status.

In sum, a review of existing literature helped identify the key channels through which adoption of modern agricultural technologies and improved practices affected general welfare at individual or household levels. A review of literature on adoption of high yield varieties of seeds, extension services, and fertilizers applied to the production of different agricultural crops in different countries in Africa, Asia, and Latin America showed that in general, adopting agricultural technologies had a positive and significant effect on household welfare, national food security, and children's nutrition. By using improved and updated data and methods this study adds to existing knowledge in the field.

3. Impact Evaluation Challenges and Estimation Strategies

Assessing and estimating the impact of technology adoption on households' welfare outcome variables based on non-experimental observations is not a straightforward task. A program's impact assessment in such a setting is equivalent to assessing the causal effects of the program on a series of welfare indicators. In an impact evaluation, a person may be either in the treated or in the control group, but not in both (Heckman et al., 1997). In the technology adoption framework, this means that the outcome variables of households that adopt would not be observed had they not adopted the technologies. In an experimental setting, this problem is addressed by randomly assigning adoption to treatment and control status and thus the welfare indicator's variables observed in the control households that do not adopt are taken as representative of what would have happened to the adopters if they had not adopted the technology.[21]

An experimental data can provide information on the counterfactual situation that will solve the problem of causal inference which is a fundamental problem in non-experimental studies. Becker (2009) states that the basic challenge of impact evaluation is causal inference and he shows that it is not uncommon to observe for the same unit i the values $W_i=1$ and $W_i=0$ and similarly the outcome values $Y_i(1)$ and Y_i (0) and thus, it is not possible to observe the effect of W on Y for unit i.[22]

D'Agostino (1998) argues that in studies that use a non-randomized design one cannot control the treatment assigned which shows that the results of a simple direct comparison of outcomes from the treatment group become misleading. This difficulty may be partially avoided if information on measured covariates is incorporated into the study design through different estimation approaches. Similarly, Asfaw and Shiferaw (2010) state that analyzing the welfare influence of agricultural technologies is linked to two common challenges: unobserved heterogeneity and possible endogeneity problems that need a correct formulation of the program's effects. Thus, the differences in a welfare outcome's variables between those farm households that did and those that did not adopt improved technology could be due to unobserved heterogeneity. If the unobserved

[21]Another way of expressing this problem is by saying that we cannot infer the effect of a treatment because we do not have the counterfactual evidence, that is, what would have happened in the absence of treating the same individual who has been treated.

[22] W is the treatment indicator variable and Y is the (welfare) outcome variable.

heterogeneity is not correctly accounted for, it may lead to inappropriate policy evaluations and implications.

In addition to this, Amare et al. (2012) and Asfaw et al. (2012b) explain that adoption is not randomly distributed among the two groups of treated and not treated, but rather households make their own adoption choices and thus, the two groups may be systematically different. Therefore, possible self-selection due to observed and unobserved household characteristics makes the assessment of real welfare impacts of technology adoption using observational data difficult. If we fail to correctly account for this potential selection bias, it could lead to inconsistent estimates of the impact of technology adoption.

As suggested by Hausman (1978), the easiest method of examining the impact of the adoption of improved technologies on welfare outcome indicators is by including a binary variable equal to 1 if the farm household has adopted a new technology or 0 otherwise in the welfare equation and then estimating the impact using the ordinary least squares (OLS) method. But the basic problem here is that this approach might yield biased estimates because it assumes that adoption of the improved technology is exogenously determined while it is potentially endogenous. The decision to adopt or not is voluntary and is taken based on an individual self-selection process. Farmers who have adopted a technology may have systematically different characteristics compared to farmers who have not adopted the technology. The former may have decided to adopt the improved technology based on expected adoption benefits.

4. Methodology

4.1 Conceptual Framework of Adoption Decision and Impact Evaluation

If the base of a study is the farm household level, welfare impacts of agricultural technologies primarily occur through adoption at the decision stage of a farmer household. Welfare changes are directly felt by adopters through higher gains in, for example, crop production and lower production costs, which in turn lead to higher own consumption and disposable incomes. Zeng et al. (2015) state that to show the link mathematically and to quantify these relationships for estimation purposes, it is possible to apply a typical impact evaluation framework in which adoption is seen as a treatment and food security of the whole household and the nutritional status of children are the observed welfare indicator outcome variables.

In addition to production choices of available technologies, households also have to take consumption decisions. Households are assumed to maximize their utility function subject to budget constraints. Applying a random utility framework method, households decide to adopt a technology if the adoption increases their utility levels. The difference between the utility of adoption (U_{iA}) and non-adoption (U_{iN}) of the technology is given as W* such that the utility maximizing farm household *i* will choose to adopt the technology if the utility gained from adopting it is greater than the utility of not adopting the specified technology which is given by $\left(W^{*} = U_{iA} - U_{iN} > 0\right)$. However, the two utilities are unobservable (as discussed in Section 3 as a challenge of impact assessment); they can be expressed as a function of observable components in the latent variable model as:

$$(1) \qquad W_{it}^{*} = \beta\tau_{it} + u_{it}, with \;\; W_i = \begin{cases} 1 & if \; W_i^{*} > 0 \\ 0 & otherwise \end{cases}$$

where W is a binary 0 or 1 dummy variable for the use of new technology; W=1 if the technology is adopted and W = 0 otherwise. β is a vector of the parameters to be estimated, τ is a vector that represents household characteristics, t is time (year dummies), and u is the random error term with mean zero and constant variance.

Because of this unobservable problem of the two utilities at a time, a method that controls for systematic differences between the households in the treated and control groups is important (Bucheli et al., 2016). Evaluating the impact of technology adoption on household welfare using ordinary least squares may lead to parametric biases as the decision to adopt a technology may not only be due to observed characteristics and even unobservable factors may also affect the decision. In literature, impact evaluations generally use a variety of econometric approaches for addressing selection bias issues that may arise with non-experimental designs.

The first empirical modeling approach that this study adopts is the two-way fixed-effects (FE) error component structure method which is a flexible approach that allows us to estimate treatment effects considering differing adoption times. We use the fixed-effects model to eliminate the effects of observable and unobserved household heterogeneity, but fixed over time, as a source of bias in estimates of the technologies' impacts. But commonly the fixed effect error structure only incorporates the potential influence of time-invariant unobservables.

To address some limitations of the FE approach, we complemented the analysis by employing other methods that take into account the selection bias both from observable and unobserved factors. These methods include the propensity score matching (PSM) and endogenous treatment effects (ETE) models. We used the non-parametric regression method PSM to assess the robustness of the results. Matching is a widely used non-parametric estimation technique of impact evaluation. It is based on the intuitively attractive idea of contrasting the outcomes of the program's participants (denoted by Y_1) with the outcomes of 'comparable' non-participants (denoted by Y_0). Differences in the outcomes between the two groups are attributed to the program's effects (Heckman et al., 1998).

Propensity score matching is a two-step procedure. First, a probability model for adoption of an improved technology is estimated to calculate the probability (or propensity score) of adoption for each observation. In the second step, each adopter is matched to a non-adopter with similar propensity score values to estimate the average treatment effects on the treated (ATT). For the consistency of the estimated treatment effects, conditional independent assumptions must hold, namely the condition that selection in the program is independent of the outcome of participation. Several matching methods have been developed to match adopters with non-adopters with similar propensity scores. Asymptotically, all matching methods should yield the same results, even though there are trade-offs in terms of bias and efficiency in each method. However, PSM only controls for biases emanating from observed heterogeneity. Hence, we also added the endogenous treatment effects (ETE) model to consider the endogeneity of households' adoption decisions (Heckman, 1976, 1978; Maddala,1983; Wooldridge, 2010).

4.2 Model Specification

The two-way fixed-effects error component structure is given by:

(2) $$y_{it} = \alpha_0 + \beta X_{it} + \theta W_{it} + \alpha_i + \varepsilon_t + \mu_{it}$$

where y_{it} is the outcome variable (food security in terms of calorie intake and child nutrition indicators in this case) for household i in the adoption category at time t, W is the treatment indicator factor which equals 1 if the household is an adopter and 0 otherwise. α_i are household fixed effects, ε_t are the year effects or wave fixed effects, and μ_{it} is the random error term. X_{it} is a vector of household characteristic and θ is the impact of interest in our case, or a factor that captures the average treatment effects.

In the second estimation technique, following Cameron and Trivedi (2005); Greene (2012); Heckman (1976, 1978); Maddala (1983); and Wooldridge (2010) we specify the endogenous treatment effects (ETE) model as:

(3) $$y_{it} = \alpha_{it} + \delta W_{it} + \beta X_{it} + \varepsilon_{it}$$

$$\text{where } W_{it}^* = \beta \tau_{it} + u_{it}$$

where τ_{it} are the covariates used to model the treatment assignment (the three technologies in our case), and the error terms ε_{it} and u_{it} from Equations (1) and (3), are bivariate normal with mean zero and the covariance matrix is given as:

$$cov(\varepsilon_{it}, u_{it}) = \begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}$$

It should be noted that the covariates X_{it} and τ_{it} are unrelated to the error terms; in other words, they are exogenous. We call this the constrained model because the variance and correlation parameters are identical across the treatment and control groups.

Where σ^2 is the variance of disturbance term (ε) in the main outcome regression Equation (3), the variance of the error term (u) in the selection or treatment Equation (1) of technology adoption*;* and $\rho\sigma$ is the covariance of ε and u. The maximum likelihood estimates provide us consistent and asymptotically efficient results. Using the maximum likelihood estimation technique, we estimate the endogenous treatment effect model with different options.

Equation (3) can be generalized to a potential-outcome model with separate variance and correlation parameters for the treatment and control groups. The generalized model is:

(4) $$y_{i0} = \beta_0 X_{i0} + \varepsilon_{i0}$$

$$y_{i1} = \beta_1 X_{i1} + \varepsilon_{i1}$$

The likelihood function for this model is discussed in Maddala (1983) and Greene (2000) and it presents the standard method of reducing a bivariate normal to a function of a univariate normal and the correlation ρ. The log likelihood function for Equations (1) and (3) for farm household i (refer to Maddala, 1983, p.122; and Greene, 2000, p.180) is expressed as:

$$lnL_i = \begin{cases} ln\Phi\left\{\frac{\beta\tau_{it} + (y_i - \beta x_{it} - \delta)\,\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_i - \beta x_{it} - \delta}{\sigma}\right)^2 - ln\left(\sqrt{2\pi\sigma}\right) W_i = 1 \\ ln\Phi\left\{\frac{-\beta\tau_{it} - (y_i - \beta x_{it})\,\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_i - \beta x_{it}}{\sigma}\right)^2 - ln\left(\sqrt{2\pi\sigma}\right) \qquad W_i = 0 \end{cases}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. In the maximum likelihood estimation method σ and ρ are not directly estimated, instead $ln\,\sigma$ and $atanh\,\rho$ are directly estimated where they are expressed as $atanh\,\rho = \frac{1}{2}\,ln\left(\frac{1+\rho}{1-\rho}\right)$.The standard error of $\lambda = \rho\sigma$is simply approximated through the delta method, which can be expressed by the following functional form: $Var(\lambda) \approx \mathbf{D}\,\mathbf{Var}\{(atanh\,\rho\; ln\sigma)\}\mathbf{D}'$ where **D** is the Jacobian of λ with respect to $atanh\,\rho$ and $ln\sigma$.

The third method that this study uses is propensity score matching (PSM) which compares the outcome of treated observations with the outcomes of comparable non-treated observations. It is defined as the conditional probability of receiving treatment given pre-treatment characteristics as:

(5) $$P(X) \equiv Pr\{W_i = 1|X\} = E\{W_i|X\}$$

where W_i = {0, 1} is the indicator of the exposure to the treatment and X is the multidimensional vector of pre-treatment household characteristics.

Rosenbaum and Rubin (1983) show that if the exposure to a treatment is random within cells defined by X, it is also random within cells defined by the values of the mono-dimensional variable $P(X)$. Let Y_{1t} be the value of the welfare outcome variable when household i is subject to treatment ($W = 1$) and Y_{0t} be the same variable when the household does not adopt the technology ($W = 0$).

As a result, given a population of units denoted by i, if the propensity score $P(X_i)$ is known, ATT can be estimated as:

(6) $$\begin{aligned} ATT &= E\{Y_{1t} - Y_{0t}|W = 1\} \\ &= E(Y_{1t}|W = 1) - E(Y_{0t}|W = 1) \end{aligned}$$

There are many important theoretical reasons (and huge empirical literature supporting the theories) why agricultural technologies might improve farm households' well-being. But the issue is how can we conclude that the adopters' better well-being compared to non-adopters is because of technology adoption (or not)? In other words, the differences between the treated and control groups could be because of pre-treatment differences, or other unobservable characteristics, or the adoption of an agricultural technology may even lead to welfare deterioration. Several available studies conclude that improved agricultural technologies act in favor of the adopters. But it should also be noted that adoption may worsen social welfare.

As the data that we use is from the same household survey for all the three types of technologies considered, the study used the same model specifications (the assumption is that households behave in almost similar ways) and the same vectors of explanatory variables.

4.3 Data Sources and Variables

The analysis is based on panel data obtained from the World Bank's Living Standard Measurement Survey (LSMS) collected in collaboration with the Ethiopia Socioeconomic Survey (ESS) Waves 2 and 3 datasets. This study used only the two recent survey datasets, 2013 and 2015, which are used for fixed effects at the household level for the sake of accuracy and availability of relevant information. The two surveys are nationally representative of rural and small towns in Ethiopia.

The data targeted the rural parts and small and medium towns in Ethiopia. The survey covered around 5,262 and 4,954 households drawn from the nine regional states and two city administrations in Waves 2 and 3 respectively. Households from both small and medium towns were excluded because of non-applicability of agricultural technology adoption. The study considered three types of agricultural technologies and improved practices -- row planting or recommended spacing, improved seeds (high yielding variety seeds, HYVs), and chemical fertilizers. Separate data was organized for each type of technology for simplicity and ease of analysis. After controlling and accounting for missing observations and non-applicable households, the sample size for row planting technology was 3,875 while 5,295 households were taken for the HYVs category and 5,806 households were considered for chemical fertilizers.

As the focus of this study is identifying the impact of improved agricultural technologies on food security and child nutrition, four outcome variables were used for evaluating the impact of these technologies: household per capita food consumption expenditure, average food intake per day per child, self-response to food shortages in households, and self-response to whether a household worried about the availability of food or not.

One of the challenges in relation to the data was absence of information on the child nutrition indicator. The plan was to use either anthropometric measurement indicators like height and weight and circumference and length of various body regions or the body mass index (BMI) but none of this information was included in the survey. A possible and available option was using the average food intake per day per child and its variety as a possible proxy for child nutrition.

5. Empirical Results

5.1 Results of the Descriptive Analyses

This study considered three different types of agricultural technologies and improved practices. In the first case, adopters of the agricultural technology were farm households who planted either improved or local (traditional) seeds in recommended spacing (row planting). The non-adopters were those who did not use the row planting method (used broadcasting technique) in any of the improved or local varieties. Thus, farmers who were experienced in growing local/improved seed varieties using the common broadcast method were considered as non-adopters. Considering the second technology adoption, we classified adopters as households who planted any of the improved high yielding varieties (HYVs) and non-adopters as those who planted any of the local (traditional) varieties. The final type of technology investigated is chemical fertilizers' adoption. Again, adopters were households who used any type of chemical fertilizers while non-adopters were those who planted crops without applying any type of chemical fertilizers.

Using three different agricultural technologies enabled us to compare and identify which technology was highly associated with welfare enhancement and had a more powerful impact on social well-being and related measures. It also showed which areas of the agriculture sector needed interventions by policymakers or extension service workers as part of their development programs. Most previous studies use a single agricultural technology and do not compare multiple and simultaneous impacts of different technologies or improved practices. Thus, an analysis and comparison of multiple sources of welfare and well-being is a contribution of this study.

This section gave the descriptive statistics of the food security and child nutrition analysis. Summary statistics and tests of statistical significance on equality of means for continuous variables and equality of proportions for binary variables for adopters and non-adopters are given in Table 1 (in the Appendix). The descriptive statistical summary in this table shows that adopter households on average had more per capita food consumption expenditure, (4,120 Birr per year per adult equivalent), which is significantly higher than the per capita food consumption expenditure of non-adopters (3,360 Birr). After transforming the per capita food consumption expenditure into a logarithm form, the test also showed that there existed significant differences between adopters and non-adopters in per capita food consumption. Although we found statistically insignificant results, non-adopters as compared to adopters faced food shortages and worried about the availability of enough food throughout the year based on self-reported subjective responses.

[Insert Table 1 about here]

Concerning child nutrition, measured by the average food intake per day per child, on average adopter households had a higher food intake in which a child eats food 3.9 times per day as compared to 3.7 times per day among non-adopters. Similarly, the logarithmic form showed statistically significant differences in the two groups. So, we prove that there is a difference in consumption per capita and child nutrition, though it is early to conclude this between adopters and non-adopters.

Looking at the other characteristics and control variables, we observed that adopters had higher education levels measured at above grade 6, were older as both age and age squared indicated, had higher access to credit, received more information on sowing seeds following recommended spacing, and had more access to electricity as a source of light. On the other hand, non-adopter households had more livestock holdings and used more crop rotation methods for planting seeds which perhaps may be the reason for their not using row planting. The non-adopter group was also significantly distinguishable in terms of using firewood, such that they used more firewood as a source of cooking fuel, and most of them followed non-orthodox religions making them statistically different from the adopters. In this preliminary analysis, it is possible to observe that there were some significant differences between the adopters and non-adopters when it comes to the specified technologies. But, the big challenge of such an analysis is identifying and evaluating if these differences are due to the technologies or other pre-treatment characteristics. To identify and quantify these differences, or more formally to find the impact of the technologies, we used FE and PSM methods for our analysis.

5.2 Econometric Results

Before estimating the causal effects of improved agricultural technologies, we tested the quality of the matching process. The matching methods were tested, and they passed different quality checking tests. After estimating the propensity scores for the adopter and non-adopter groups the common support condition was checked. A visual inspection of the density distributions of the estimated propensity scores for the two groups (see Figures 1-3 in the Appendix) shows that the common support condition was satisfied: there was substantial and considerable overlap in the distribution of the propensity scores of both adopters and non-adopters for all the three technologies. The bottom half of the figures show the propensity scores' distribution for the non-adopters and the upper half shows it for the adopters; the densities of the scores are on the y-axis.

[Insert figures 1-3 about here]

The other test was the imbalance between the treatment and control groups on the covariates including the propensity score. The imbalance between the groups in terms of the propensity score was around 98 percent before matching for the three technologies (not reported here because of its large size).[23] This bias was significantly reduced (well below 3 percent) after matching. The test shows that before matching several variables exhibited statistically significant differences, while after matching the covariates were balanced which shows the efficiency of the PSM method and guarantees that we can match the two groups based on those common support restricted areas.

The third tests used were the covariate balancing tests before and after matching as reported in Table 2 in the Appendix. The standardized mean difference for overall covariates used in the propensity score for the three technologies (around 8.4 percent before matching) reduced to around 3.2 percent after matching. The p-values of the likelihood ratio tests show that the joint significance of the covariates was always rejected after matching, whereas it was never rejected before matching. The pseudo R^2 also dropped significantly from around 1.2-4 percent before matching to about 0.3 - 1.1 percent after matching under the three technologies. The likelihood ratio test was also statistically significant before matching for all the three technologies but became insignificant after matching. The low pseudo R^2, high bias reduction, and the insignificant p-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score was successful in terms of balancing the distribution of covariates between the two groups.

[Insert Table 2 about here]

For the first technology type, recommended spacing is considered as a treatment indicator variable. Table 3 gives the estimated FE and the results show that adoption of row planting highly increased per capita consumption expenditures of the adopters in all the cases, with and without control estimations, through Models 1 to 4. The overall average gains of adopting the technology on per capita consumption expenditure ranged from about 605 to 756 Birr under the four models.

In the first FE model's specifications in Table 3 we included the treatment status of households and the observation period's variables. In the second model, personal and household characteristics were added with treatment and time variables. In the third model, we incorporated variables indicating access to social services along with credit and extension provisions. In the fourth FE regression model, we included other controls indicating households' asset ownership. As we included more and more controls at different levels, the added variables did not substantially change the estimated treatment effect of the technology. This alleviates concerns that unobserved characteristics are confounding our estimates, although we needed to check this through the PSM estimation method which we did.

[23] The reported results are based on the nearest neighbor matching (NNM) method. Although not reported, these results are the same using the other matching methods. Similarly, the following tests are from the NNM method.

[Insert Table 3 about here]

The results showed that there was a strong impact of technology on food security. For example, under Model 1 reported in Table 3, the per capita consumption expenditure of the adopters was higher by about 756 Birr as compared to non-adopters and the result was statistically significant. The average increase in per capita consumption expenditure in all the four FE models was statistically significant. Thus, these results show that there is a positive and significant impact of adopting this technology on food security, even with more and more additional controls.

For ease of interpretation and to avoid a possible rightward skewness, the consumption expenditure was transformed into logarithms; the estimated impact of row planting on this transformed per capita consumption expenditure was found to be statistically significant. The estimated results reported in Column 1 of Table 4 show that per capita consumption expenditure was about 10 percent higher for the households which used the row planting method as compared to households that used the broadcast method of sowing seeds. A similar result was also obtained for child nutrition. The overall average gain in child nutrition measured by the number of food intakes per child per day was significantly higher for the adopters.

[Insert Table 4 about here]

Children in the technology adopter household group had increased food intake per day of about 6 percent due to the improved agricultural technologies (see Table 4, Column 2). However, it was observed that there was no association between row planting and the remaining two outcome variables, self-response on food shortages and whether households worried about the availability of food, as the results in the last two columns of Table 4 show. Thus, adoption of row planting is not linked to a statistically significant change in solving problems related to food shortages and households' fears about the availability of enough food throughout the year.

We also used the PSM and endogenous treatment effects (ETE) methods in combination with FE to check the consistency of the output in the different estimation techniques. Table 5 gives the results of all the three estimation methods on the impact of row planting on food security measured by consumption expenditure and in the case of PSM the results are reported using four matching methods -- nearest neighbourhood matching (NNM), kernel matching (KM), radius matching (RM), and stratification matching (SM) --- while in the ETE approach we used estimation techniques including inverse-probability weighted (IPW), inverse-probability weighted regression adjustment (IPWRA), and linear regression with endogenous treatment effects (LRETE).

[Insert Table 5 about here]

From Table 5 it can be seen that when using FE, average consumption per capita of the technology adopter households increased by about 756 Birr. Similarly, using the log of consumption per capita as an outcome variable, the results show that technology adoption increased per capita consumption by about 13 percent. The increase in child nutrition was also significant and higher for technology adopters by about 5 percent.

Similar results were obtained using PSM and ETE methods with different estimation options in both the cases. The overall average gain of per capita consumption expenditure of adopting improved agricultural technology using the PSM method ranged from 633 to 750 Birr under the four algorithms, while using ETE the gain ranged from about 644 to 649 Birr under the three estimation options and all of them were statistically significant. This measures the average difference in consumption expenditure of similar pairs of households that had different technological status. This indicates that per capita consumption expenditure for farmers who adopted row planting was significantly higher than that for non-adopters.

Concerning the second technology type, adoption of HYVs, households were categorized as adopters or non-adopters based on the type of seeds that they used. Table 6 gives the impact of HYVs obtained using the FE method on food security measured by consumption expenditure. The results show that adoption of HYVs highly increased adopters' per capita consumption expenditure. Looking at the impact conditioned on controlling for other factors, the FE results show a 707 Birr increase in per capita consumption expenditure for adopter households. This is equivalent to a 10 percent increase in per capita consumption expenditure which is statistically significant. This result supports the descriptive statistical analysis discussed earlier and shows that there was a significant difference in per capita food consumption between adopter and non-adopter households. The estimated results also show that adoption of HYVs improved child nutrition by about 6 percent.

[Insert Table 6 about here]

Like for the first technology type, row planting, we estimated the fixed effects model with different specifications for HYVs. In Table 6, we include the treatment status of households and the observation period variables in Column 1, in the second column we add household characteristics with treatment and time variables, in the third column under Model 3 we have incorporated variables indicating access to social services like credit and extension provisions, and finally in the fourth FE regression model we incorporate control variables indicating households' asset ownership. The inclusion of more control variables did not change the estimated treatment effects of technology adoption.

The PSM and ETE methods' results also show that the per capita consumption expenditure of adopters of HYVs increased in the range of 532 to 617 Birr and 554 to 749 Birr respectively in the two methods. In other words, this is equivalent to an increase in the estimated impact of HYVs on the transformed per capita consumption from 6 to 9 percent using PSM and 7 to 35 percent using ETE for adopters as compared to non-adopters and the result is statistically significant. The estimated results for child nutrition also suggest that on average daily food intake for children in households that adopted HYVs increased in the range of 7 to 8 percent in the case PSM and 8 to 20 percent in the case of ETE as indicated on the last column of Table 7.

[Insert Table 7 about here]

The final technology type is adoption of chemical fertilizers. Table 8 shows the fixed effects' estimation results. It shows that chemical fertilizers improved food security measured by per capita consumption expenditure. Adopters increased their per capita consumption expenditure by about 437 Birr due to the use of chemical fertilizers in planting crops. We also estimated FE with the inclusion of control variables like household characteristics and access to assets and services, and the results remained robust and consistent throughout.

[Insert Table 8 about here]

In general, households that adopted chemical fertilizers improved their food consumption expenditure through more yields leading to higher revenues and good access to social services that are linked to having more income. According to this result, fertilizer adoption raised adopters' per capita consumption by about 1 percent on average as compared to the non-participants, though the transformed per capita consumption had an insignificant effect (see Table 9).

Table 9 shows that using the three estimation methods led to the same conclusions that the adoption of chemical fertilizers had a positive and significant impact on per capita consumption of adopter households. However, the results in percentage change show that the impact was slightly different between the methods. According to the results using PSM and ETE methods, adoption of chemical fertilizers increased per capita consumption of adopter households in the range of 3 to 7 percent and 4 to 6.8 percent respectively on average as compared to non-participants. The impact using fixed-effects regression showed statistically insignificant results for per capita consumption in percentage points.

[Insert Table 9 about here]

Further, the results led to the same results concerning the impact on child nutrition. According to the PSM method, adoption of chemical fertilizers raised child nutrition in adopter households by about 55 percent on average as compared to non-participants, while the impact using fixed-effects and ETE regressions showed a 56 percent increase in child nutrition.

Concerning the remaining two of our outcome variables - food shortages and whether a household worried about the availability of food or not - there was no strong support that showed the impact of the adopted technologies. This shows that technology adoption did not create differences between adopters and non-adopters concerning food shortages and availability.

In general, the results of the fixed-effects, PSM, and ETE methods showed that the three improved agricultural technologies significantly affected household food security and child nutrition. When we used these estimation methods to consider the impact of these technologies, the results almost consistently produced significant differences between adopters and non-adopters. The results using these methods also showed that the technologies considered increased both household food consumption expenditure and child nutrition.

The summary results of all the three estimation methods for the two major outcome variables - consumption expenditure and child nutrition - under all the three technologies are reported in Table 10. This table helps us to see the benefits and limitations of the approach to facilitate ways of comparing the results. For food shortages and whether a household worried about the availability of food or not, the estimation results show that there was no link to any of the stated technologies and so these results are not reported.

[Insert Table 10 about here]

6. Conclusion

This study explored the potential impact of adopting improved agricultural technologies and practices including row plantation, using high yield varieties (HYVs) of seeds, and chemical fertilizers on rural household food security and child nutrition. The estimation results of all the FE, PSM, and ETE methods showed that adoption of improved agricultural technologies had a robust, significant, and positive impact on per capita consumption expenditure and child nutrition.

Regarding the results obtained from adopting the row planting technology, the average increase in per capita consumption expenditure in all the four FE models was statistically significant. The per capita consumption expenditure of adopters was higher by about 756 Birr as compared to the non-adopters. Our study also showed that children in the technology adopter household group had increased food intake per day by about 6 percent compared to children in the non-adopter group. Similar results were obtained using the PSM method with different matching algorithms. The overall average gain of per capita consumption expenditure of adopting improved agricultural technologies ranged from 633to 750 Birr under the four algorithms and all of them were strongly significant at a less than 1 percent probability level, and similar results were obtained using the ETE approach as well.

The study also investigated the impact of HYVs on the welfare of rural households and the results showed that adopting improved varieties resulted in highly increased per capita consumption expenditures among the adopters. The FE method's results showed that the adopters had a 707 Birr increase in per capita consumption expenditure while the PSM method's results showed that per capita consumption expenditure among the adopters of HYVs increased in the range of 532 to 617 Birr under the four matching methods and about 554 to 749 Birr in the case of the ETE method. The estimated results of child nutrition also show that on average daily food intake for children in households that adopted HYVs increased in the range of 7 to 8 percent.

Looking at the estimated technology adoption results for fertilizers, using all methods led to the same conclusions that the adoption of chemical fertilizers had a positive and significant impact on per capita consumption of adopter households. Further, the results of all the methods led to the same conclusions concerning the impact on child nutrition.

Overall, our results showed that there was a positive and significant impact of using improved technologies on food security and child nutrition. Concerning the remaining two of our four outcome variables -food shortages and whether a household worried about the availability of food or not -- there was no strong support in favor of the impact of these technologies. This indicates that adopting these technologies did not create differences between the two groups concerning food shortages and availability.

7. Policy Implications

Our results show that there is a positive and significant impact of improved agricultural technologies on food security and child nutrition. These results also suggest the need for continued and broad public and private investments in agricultural research and different technologies to address important development challenges; the results also show that policy support for improving extension efforts and access to seeds and market outlets that simulate adoption of improved agricultural technologies are needed.

Exploiting the full benefits of technology in improving food and nutritional security will require increased investments and policy support for improving agricultural productivity through a variety of services like access to information, access to credit and extension support and field visits, supply of complementary inputs such as pesticides and herbicides, better producer prices, and developing the value chain for reducing transaction costs related to input and output markets since these factors are highly linked to agricultural technologies and the decision to adopt them.

The higher benefits for non-adopters had they adopted the technologies indicate the existence of other limiting factors and barriers to adoption including information gaps. These are often related to information about and access to seeds and fertilizers. Hence, development policies for agricultural transformation in Ethiopia need to remedy this situation and aggressively increase access to, and use of, modern agricultural technologies. This study suggests that such investments will have a substantial impact on improving households' food security and reducing hunger and poverty in rural Ethiopia.

A one-time trial or use of an agricultural technology can hardly change livelihoods, reinforcing the need for using technologies on a continuous basis. Given that farmers' variety-attribute preferences determine both their propensity to use improved varieties and the chances of using them successfully, breeding should satisfy the demands of different farm household types classified according to resource endowments, preferences, and constraints. To this end, analyzing farmers' variety-attribute preferences will help target farmers' demands in developing a technology. Simply providing the technologies may create doubts in the minds of the farmers.

Adopting technologies does not make farm households feel free about the availability and surplus food in their stores. Adoption is weakly associated with food shortages and whether a household worries about the availability of food; hence appropriate interventions are needed in these areas.

References

Adekambi, S. A., Diagne, A., Simtowe, F., & Biaou, G. (2009). The Impact of Agricultural Technology Adoption on Poverty: The Case of, NERICA Rice Varieties in Benin. Contributed paper prepared for presentation at the International Association of Agricultural Economists' conference, Beijing, China, August 16-22, 2009.

Amare, M., Asfaw, S., & Shiferaw, B. (2012). Welfare impacts of maize–pigeon pea intensification in Tanzania. *Agricultural Economics*, *43*(1), 27-43.

Asfaw, S., & Shiferaw, B. (2010). Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Poster presented at the 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19 – 23, 2010

Asfaw, S., Kassie, M., Simtowe, F., & Leslie, L. (2012b). Poverty Reduction Effects of Agricultural Technology: A Micro-evidence from Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Asfaw, S., Shiferaw, B., & Simtowe, F. (2010). Does technology adoption promote commercialization? Evidence from chickpea technologies in Ethiopia. In *CSAE 2010 conference on Economic Development in Africa, University of Oxford, UK*.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012a). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295.

Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: a propensity scores matching approach. *World Development, 38*(7), 1024-1035.

Becker, S.O. (2009). *Methods to Estimate Causal Effects Theory and Applications. U Stirling, Ifo, CESifo and IZA last update: 21 August 2009.* UK: Stirling Management School.

Bond, C. A., Carter, C. A., & Farzin, Y. H. (2005). *Economic and Environmental Impacts of Adoption of Genetically Modified Rice in California.* Giannini Foundation Research Report #350. University of California: Institute of Agriculture and Natural Resources.

Braun, J.V. (1988). Effects of Technological Change in Agriculture on Food Consumption and Nutrition: Rice in West African setting. *World Development*, 16(9), 1083-1098.

Bucheli, J. R., Bohara, A. K., & Villa, K. (2016). *The Impact of a Rural Road Development Project on Multidimensional Poverty in Nepal*. Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, and July 31-August 2.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.

D'Agostino Jr, R. B. (1998). Propensity score methods for bias reduction in the comparison of a treatment to a non-randomized control group. *Statistics in medicine*, *17*(19), 2265-2281.

Faltermeier, L., & Abdulai, A. (2006). The Adoption of Water Conservation and Intensification Technologies and Farm Income: A Propensity Score Analysis for Rice Farmers in Northern Ghana, Annual Meeting, July 27-29, Orlando, Florida, American Agricultural Economics Association.

FAO (Food and Agriculture Organization of the United Nations) (2015). *The state of food security in the World*. Rome: Food and Agriculture Organization of the United Nations.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, *33*(2), 255-298.

Feleke, S., & Zegeye, T. (2006). Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food policy*, *31*(5), 442-457.

Ferede, S., Teklewold, H., & Ayele, G. (2003). Impact of Technology on Households Food Security, in Tef and Wheat Farming Systems of Moretna_Jiruworeda. Ethiopian Agricultural Research Organization (EARO), Research Report No.48.

Greene, W. H. (2000). *Econometric Analysis*, 4th edition. Upper Saddle River, NJ: Prentice Hall.

Greene, W. H. (2012). *Econometric Analysis*, 7th edition. *Stern School of Business, New York University*.

Hagos, F., Jayasinghe, G., Awulachew, S.B., Loulseged, M., & Yilma, A.D. (2012). Agricultural water management and poverty in Ethiopia. *The Journal of the International association of Agricultural Economics*, 43, 99–111.

Hausman, J.A. (1978). Specification tests in econometrics. *Econometrica*, 46, 1251-1272.

Heckman, J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, 5, 475–492.

Heckman, J. (1978). Dummy endogenous variables in a simultaneous equation system. *Econometrica*, 46, 931–959.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, *64*(4), 605-654.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). *Characterizing selection bias using experimental data*. *Econometrica*, 66(5), 1017–1098.

Hossain, M. (2009). *The impact of shallow tubewells and boro rice on food security in Bangladesh* (No. 917). International Food Policy Research Institute (IFPRI).

Hundie, B., & Admassie, A. (2016). “Potential Impacts of Yield-Increasing Crop Technologies on Productivity and Poverty in two Districts of Ethiopia”, in F. Gatzweiler and J. von Braun (eds), *Technological and Institutional Innovations for Marginalized Smallholders in Agricultural Development.* Springer International Publishing (pp. 397-421).

Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda. *Environment for Development Discussion Paper-Resources for the Future (RFF)*, (10-11).

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World development*, *39*(10), 1784-1795.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, 66, 695–706.

Kumar, N., & Quisumbing, A. R. (2011). Access, adoption, and diffusion: understanding the long-term impacts of improved vegetable and fish technologies in Bangladesh. *Journal of Development Effectiveness*, *3*(2), 193-219.

Langyintuo, A. S., Diallo, W. M., MacRobert, A. O., Dixon, J., & Banziger, M. (2008). *An Analysis of the Bottlenecks affecting the production and deployment of maize seed in eastern and southern Africa*. CIMMYT.

Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

Mendola, M. (2003). Agricultural technology and poverty reduction: A micro-level analysis of causal effects. *Centro Studi Luca D'Agliano Development Studies Working Paper*, (179), November, University of Milan-Bicocca, Italy.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy*, *32*(3), 372–393.

Moyo, S., Norton, G. W., Alwang, J., Rhinehart, I., & Deom, C. M. (2007). Peanut research and poverty reduction: Impacts of variety improvement to control peanut viruses in Uganda. *American journal of agricultural economics*, *89*(2), 448-460.

Muzari, W., Gatsi, W., & Muvhunzi, S. (2012). The Impacts of Technology Adoption on Smallholder Agricultural Productivity in Sub-Saharan Africa. *Journal of Sustainable Development*, 5(8), 69-77.

Odame, H., Alemu, D., Kimenye, L., Kabutha, C., & Oduori, L. H. (2013). *Why the Low Adoption of Agricultural Technologies in Eastern and Central Africa?* Association for Strengthening Agricultural Research in Eastern and Central Africa.

Ogada, M. J., Mwabu, G., & Muchai, D. (2014). Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions. *Agricultural and food economics*, *2*(1), 12.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica*, *70*(1), 41-55.

Rubas, D. J. (2004). *Technology adoption: who is likely to adopt and how does the timing affect the benefits?* (Doctoral dissertation, Texas A&M University).

Sahu, S. K., & Das, S. (2016). Impact of agricultural related technology adoption on poverty: A study of select households in Rural India. In *Technology* (pp. 141-156). Springer, Singapore.

Salazar, L., Aramburu, J., González-Flores, M., & Winters, P. (2015). Food security and productivity: impacts of technology adoption in small subsistence farmers in Bolivia. Inter-American Development Bank (IDB) Working Paper Series 567.

Sanchez, P. A., Denning, G. L., & Nziguheba, G. (2009). The African green revolution moves forward. *Food Security*, *1*(1), 37-44.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272-284.

Simon, M. (2013). Estimating the role of agricultural technologies in improving rural household welfare: A case of Masvingo. *Russian Journal of Agricultural and Socio-Economic Sciences*, 14(2), 67–73.

Swanson, B. E., & Rajalahti, R. (2010). Strengthening Agricultural Extension and Advisory Systems: Procedures for Assessing, Transforming, and Evaluating Extension Systems, The World Bank Agriculture and Rural Development Discussion Paper 45, Washington DC.

The World Bank (2008). *World development report 2008: agriculture for development.* Washington, DC: The World Bank.

The World Bank (2015). *World Development Indicators*. Washington, DC: The World Bank

Tigabu, D. G., & Gebeyehu, M. F. (2018). Agricultural Extension Service and Technology Adoption for Food and Nutrition Security: Evidence from Ethiopia. *Forum for Agricultural Research in Africa (FARA) Research Report*, 3(4), 30.

Wanyama, J. M., Nyambati, E. M., Mose, L. O., Mutoko, C. M., Wanyonyi, W. M., Wanjekeche, E., & Rono, S. C. (2010). Assessing impact of soil management technologies on smallholder farmers' livelihoods in North Western Kenya. *African Journal of agricultural research*, *5*(21), 2899-2908.

Wanyama, J.M., Nyambati, E.M., Njuki, J., Mose, L.O., Mutoko., C.M., Wanyonyi, M., Mwangi, T., Wanjekeche, E., Ndung'u, K.N., Rono, S., Simanto, O., & Wachiye, B. (2005). Impact of Soil Management Project Technologies on Farmers' Livelihoods in North Rift Province of Kenya. *KARI Biennial Scientific Conference*, Nairobi (Kenya), November 12 - 17.

Weisenfeld, P., & Wetterberg, A. (2015). Technological Advances to Improve Food Security: Addressing Challenges to Adoption Press: Research Brief. *Addressing challenges to adoption*. (RTI Press Publication No. RB-0011-1510; No. RB-0011-1510). Research Triangle Park, NC: RTI Press.

Woog, J.P. (2008). The Potential Impact of Advanced Maize Genomic Technology on Corn Cultivation in Northern China. Mayo High School Rochester, Minnesota.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. 2nd edition. Cambridge, MA: MIT Press.

Wu, H., Ding, S., Pandey, S., & Tao, D. (2010). Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching analysis in rural China. *Asian Economic Journal*, *24*(2), 141-160.

Yu, B., Nin-Pratt, A., Funes, J., & Gemessa, S. A. (2011). *Cereal production and technology adoption in Ethiopia* (Vol. 31). Internat. Food Policy Research Institute.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2015). Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics*, *46*(4), 515-526.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2014). Agricultural Technology Adoption and Child Nutrition: Improved Maize Varieties in Rural Ethiopia. Selected Paper prepared for presentation at the Agricultural and Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Appendix

Table 1[24]: A Description of the variables by type for row planting technology

Variables	Description	Adopter	Non-adopter	t-stat/Chi-square
Outcome variablers:				
Consexp	Per capita food consumption expenditure (in Birr)	4,120.11	3,360.29	759.82(5.82) ***
Lnconsexp	Natural log of consumption expenditure	8.04	7.91	0.13(4.47) ***
Child nut	Child nutrition based on average food intake per day per child	3.91	3.72	0.19(3.71) ***
Lnchild nut	Natural log of child nut	1.38	1.33	0.05(5.60) ***
Worry food	HH care about availability of food based on subjective response (1 = worry)	0.16	0.17	-0.01(0.22)
Food shortage	HH faces food shortages based on subjective response (1 = yes)	0.31	0.32	-0.01(0.29)
Treat ind. Variable:	Treatment indicator variable			
Row planting	Household adopted row planting method (1 = yes)	0.15	0	1
Expl. Variables:	Explanatory variables			
Region	Region dummy(1=Amhara)	0.26	0.25	0.01(0.06)
Age	Age of HH head (years)	47.33	46.29	1.04(1.59) *
Age^2	Squared value of age of HH head (years)	2438.56	2336.41	102.41(1.56) *
Sex	Sex of the HH head (1= male)	0.81	0.82	-0.01(1.07)
Family size	Household size in adult equivalent (AE)	5.40	5.39	0.02(0.12)
Marital status	Marital status of HH head(1=married)	0.76	0.77	-0.01(0.49)
Religion	Major religion that the HHs follow(1=orthodox)	0.38	0.48	-0.10(4.35) ***
Literacy	HH head has schooling (1 = yes)	0.39	0.37	0.02(0.94)
Schooling to 6	HH head has schooling till grade 6 (1 = yes)	0.18	0.20	-0.02(1.06)
Schooling above 6	HH head has schooling above grade 6 (1 = yes)	0.15	0.10	0.05(3.53) ***
Non-farm income	HH has non-farm income sources (1= yes)	0.07	0.08	-0.01(0.54)
Livestock	Livestock ownership in TLU	0.36	0.57	0.21(4.51) ***
Oxen holding	Oxen ownership of the HH (numbers)	1.10	1.09	0.01(1.21)
Credit access	HH has access to credit services (1= yes)	0.28	0.24	0.04(2.01) **
Extension service	HH has access to extension services (1= yes)	0.72	0.69	0.03(1.45) *
Crop damage	HH has faced crop damage in the last 5 years (1= yes)	0.39	0.37	0.02(0.94)
Crop rotation	HH used crop rotation in the last year 5 (1= yes)	0.77	0.81	-0.04(2.36) **
Light source	Main source of light in the HH (1=electricity)	0.18	0.12	0.06(4.53) **
Cooking fuel	Main source of cooking fuel in the HH (1=firewood)	0.98	0.99	-0.01(2.50) **
Have phone	Any member of HH owning a cell phone (1= yes)	0.38	0.37	0.01(0.23)

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics in parenthesis. Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

[24] The same outcomes and explanatory variables are used across all technology types.

Table 2: Covariate Balance Indicators before and after Matching: Quality Test.

Technology type	Pseudo R^2 Before matching	Pseudo R^2 After matching	LR χ 2 (p – value) Before matching	LR χ 2 (p – value) After matching	Mean standardized bias before matching	Mean standardized bias After matching
Spacing	0.047	0.011	148.96(0.000)	16.77(0.725)	10.9	4.5
HYVs	0.021	0.006	99.36(0.000)	15.90(0.723)	8.2	3.2
Fertilizes	0.021	0.003	87.01(0.000)	19.99(0.333)	6.1	2.3

Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 3: FE results' spacing: Outcome variable is per capita consumption expenditure

Variable	Model 1	Model 2	Model 3	Model 4
Adoption	755.77(5.40) ***	714.16(5.16) ***	762.10(5.44) ***	604.83(2.92) ***
Observation year	175.71(2.03) **	152.40(1.74) *	175.77(2.03) **	177.91(2.00) **
Age		59.472(2.55) **		-23.85(1.21)
Age^2		-0.51(2.21) **		0.30(2.73) **
Sex		-066.21(0.40)		-190.72(1.15)
Marital status		79.97(0.52)		-70.26(0.46)
Religion		-32.27(0.32)		233.70(1.84) *
Literacy		-84.77(0.57)		103.16(0.74)
Schooling up to grade 6		-53.78(0.32)		-48.04(0.42)
Schooling above grade 6		659.19(3.18) ***		476.66(2.22) **
Family size		-220.04(8.34) ***		-269.14(10.57) ***
Credit access			-137.75(1.13)	-152.67(1.24)
Extension service			-35.86(0.32)	-12.13(0.10)
Non-farm income				76.81(81)
Livestock ownership				192.06(3.63) ***
Oxen holding				292.70(6.40) ***
Crop damage				-115.56(1.09)
Crop rotation				495.28(3.20) ***
Light source				-89.79(4.62) ***
Cooking fuel				67.22(1.29)
Have phone				-533.88(4.49) ***
Constant	3272.41(46.89) ***	2938.86(4.47) ***	3330.08(32.38) ***	3606.60(5.55) ***
Observation	3,875	3,875	3,875	3,875

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics in parenthesis.

Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 4: FE results' spacing: Outcome variables: lnconsexp, lnchildnut, Food shortage, and Worry food

Variable	lnconsexp	lnchild nut	Food shortage	Worry food
Adoption	0.10(2.88) ***	0.06 (5.91) ***	0.01 (0.39)	0.009 (0.50)
Observation year	0.07 (3.67) ***	0.01 (0.86)	0.06(4.68) ***	-0.06 (5.49) ***
Age	0.01(2.79) ***	-0.00 (0.75)	-0.00 (0.53)	-0.00 (0.19)
Age^2	-0.00 (2.30) **	0.00 (0.87)	0.00(0.23)	0.00 (0.14)
Sex	-0.05(1.28)	-0.01(0.84)	0.08 (2.66) **	0.09 (3.44) ***
Marital status	0.03 (0.73)	0.00 (0.19)	-0.04 (1.63)	-0.04 (1.75)
Religion	0.07 (2.50) **	0.00 (0.30)	0.12(5.72) ***	0.08 (4.79) ***
Literacy	-0.00 (0.03)	0.01 (0.76)	0.03(1.14)	0.01(0.44)
Schooling to grade 6	0.06(1.66)	0.00 (0.17)	0.01 (0.32)	0.01 (0.32)
Schooling above grade 6	0.12 (2.67) **	-0.00 (0.08)	0.06 (1.72) *	0.05 (1.85) *
Family size	-0.08 (13.71) ***	-0.00 (1.24)	-0.01 (1.93) *	-0.00(0.06)
Credit access	-0.01 (0.47)	0.02 (2.67) **	-0.04 (2.23) *	-0.02 (1.06)
Extension service	-0.02 (0.52)	0.02 (2.25) *	0.02(0.76)	0.02(1.12)
Non-farm income	0.06(1.47)	0.00 (0.04)	0.03 (0.98)	0.04 (1.92)
Livestock ownership	0.06 (4.11) ***	-0.01 (2.66) **	-0.01 (1.13)	0.00 (0.63)
Oxen holding	0.08(8.17) ***	0.01(3.42) ***	0.06(8.30) ***	0.05 (7.00) ***
Crop damage	-0.05(1.99) *	0.00 (0.12)	0.08 (4.16) ***	0.05 (3.18) ***
Crop rotation	0.16 (3.91) ***	-0.03(3.01) ***	0.03 (0.95)	0.01 (0.59)
Light source	-0.03 (6.01) ***	-0.01(4.54) **	-0.01 (1.67)	-0.00 (0.49)
Cooking fuel	0.01 (1.05)	-0.00(0.06)	0.02 (4.46) ***	0.01 (2.73) **
Have phone	-0.16 (6.46) ***	-0.01(1.79) *	-0.14(7.71) ***	-0.05(3.76) ***
Region	0.01(1.78) *	-0.01(3.45) ***	0.00 (0.64)	0.00 (0.26)
Constant	8.12 (48.26) ***	1.48 (30.87) ***	1.64 (13.23) ***	1.70 (17.13) ***
Observation	3,666	3,466	3,654	3,666

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics in parenthesis.

Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 5: FE, PSM, and ETE methods' Results on the impact of Spacing on the welfare of rural households

Estimation method		Outcome variables		
		Consumption expenditure	Ln Consumption expenditure	Ln child nutrition
FE		755.713(5.416) ***	0.129(3.842) ***	0.051(5.39) ***
PSM	NNM	694.974(3.15) ***	0.081(1.795) ***	0.052(4.124) ***
	RM	749.592(3.753) ***	0.142(4.462) ***	0.049(5.092) ***
	KM	706.03(4.201) ***	0.118(3.602) ***	0.049(4.385) ***
	SM	633.072(3.132) ***	0.109(3.365) ***	0.048(4.942) ***
ETE	IPW	644.41(3.23) ***	0.097(3.16) ***	0.050(5.54) ***
	IPWRA	644.13(3.21) ***	0.098(3.17) ***	0.050(5.55) ***
	LRETE	648.68(2.28) **	0.140(1.87) *	0.070(2.87) ***

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics for FE and PSM; and z-statistics for ETE in parenthesis.
Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 6: FE results for HYVs: Outcome variable is Per capita consumption expenditure

Variable	Model 1	Model 2	Model 3	Model 4
Adoption (HYVs)	707.24(3.43) ***	713.81(3.47) **	716.58(3.46) **	702.56(3.43) **
Observation year	328.40 (3.65) **	307.15 (3.79) **	342.30 (3.74) **	140.17(1.73)
Age		30.10 (1.55)		20.94 (1.14)
Age^2		-0.15(0.80)		-0.09(0.48)
Sex		-8.77(0.07)		-44.62(0.34)
Marital status		288.43 (2.51) *		295.31(2.65) **
Religion		-35.50(0.38)		212.56(2.25) *
Literacy Schooling to 6		227.14 (1.77) -14.47(0.11)		66.60(0.56) -30.14(0.23)
Schooling above 6		444.91(2.51) *		162.46(0.95)
Family size		-279.27(13.43) **		-356.80 (16.72) **
Credit access			297.64(1.84) *	64.27(0.61)
Extension service			100.63(0.73)	25.54(0.29)
Non-farm income				233.99(1.49)
Livestock				286.72(4.48) **
Oxen holding				261.42(4.64) **
Crop rotation				-362.74(3.48) **
Light source				973.49(8.31) **
Cooking fuel				-138.75(0.41)

Have phone				527.48(6.46) **
Region				-753.18(7.38) **
Constant	3,222.22 (44.31)**	3,370.15 (7.51) **	3,087.11 (24.55)**	3,838.13 (6.68) **
Observation	5,295	5,295	5,295	5,263

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 7: FE, PSM, and ETE methods' Results on the impact of HYVs on the welfare of rural households

Estimation method		Outcome variables		
		Consumption expenditure	Ln Consumption expenditure	Ln child nutrition
FE		707.24(3.43) ***	0.10(3.10) **	0.051(8.79) ***
PSM	NNM	616.68(3.67) ***	0.08(2.41) ***	0.07(6.16) ***
	RM	613.43(4.19) ***	0.09(3.42) ***	0.08(8.18) ***
	KM	589.63(4.09) ***	0.08(3.04) ***	0.07(10.08) ***
	SM	532.42(3.52) ***	0.0.06(2.50) **	0.08(8.20) ***
ETE	IPW	554.02(3.89) ***	0.068(2.94) ***	0.077(8.43) ***
	IPWRA	552.58(3.88) ***	0.067(2.93) ***	0.204(4.10) ***
	LRETE	748.53(2.59) ***	0.350(5.37) ***	0.120(2.00) **

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics for FE and PSM; and z-statistics for ETE in parenthesis.
Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 8: FE method's results for Fertilizers: Outcome variable is Per capita consumption expenditure

Variable	Model 1	Model 2	Model 3	Model 4
Fertilizer	436.82 (3.49) ***	427.04 (2.61) **	438.70 (2.36) *	430.67 (2.30) *
Observation year	-47.10 (0.31)	-68.09 (0.36)	-48.76 (0.30)	-210.601 (0.98)
Age		48.24 (0.90)		20.98 (0.33)
Age^2		-0.43 (0.77)		-0.04 (0.06)
Sex		326.83 (0.60)		457.60 (0.73)
Maritalstat		-783.08 (0.81)		-948.57 (0.89)
Religion		-315.15 (1.04)		-287.77 (0.95)
Literacy		98.19 (0.28)		79.03 (0.20)

Family size		-53.01 (0.27)		-40.33 (0.19)
Credit			-31.12 (0.07)	-71.55 (0.15)
Extension			-58.44 (0.41)	-176.84 (1.14)
Non-farm income				-575.36 (1.37)
Livestock				92.38 (0.74)
Oxenholding				219.71 (1.23)
Croprotation				87.47 (0.41)
Lightsource				252.52 (0.95)
Cookingfuel				265.16 (0.61)
Havephone				134.670 (0.51)
Constant	3,626.04 (57.36) ***	3,125.58 (2.04) *	3,667.44 (33.94)**	2,888.35 (1.48)
Observation	5,806	5,622	5,806	5,328

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 9: FE, PSM, and ETE methods' Results on the impact of fertilizers on the welfare of rural households

Estimation method		Outcome variables		
		Consumption expenditure	Ln Consumption expenditure	Ln child nutrition
FE		436.82 (2.49) **	0.01 (0.26)	0.56 (38.16) ***
PSM	NNM	721.31 (4.36) ***	0.07 (2.60) **	0.55 (26.13) ***
	RM	625.43 (4.06) ***	0.04 (2.22) **	0.55 (39.98) ***
	KM	617.98 (3.87) ***	0.04 (2.63) **	0.55 (10.08) ***
	SM	588.71 (3.79) ***	0.0.03 (1.65) *	0.55 (37.62) ***
ETE	IPW	617.42(4.05) ***	0.040(2.28) **	0.551(39.13) ***
	IPWRA	609.96(4.00) ***	0.039(2.19) **	0.556(39.60) ***
	LRETE	595.71(1.39)	0.068(10.57) ***	0.570(36.17) ***

Note: Statistically significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively. Absolute values of t-statistics for FE and PSM; and z-statistics for ETE in parenthesis.
Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

Table 10: Summaries of FE, PSM, and ETE methods' Results for the three technologies

Estimation method	Technology types					
	Spacing Outcome variables		HYVs Outcome variables		Fertilizers Outcome variables	
	Lnconexp[25]	Lnchildnut[26]	Lnconexp	Lnchildnut	Lnconexp	Lnchildnut
FE	0.129 ***	0.060 ***	0.100 ***	0.051 **	0.010 **	0.560 ***
PSM	0.081 ***	0.052 ***	0.080 ***	0.070 ***	0.070 ***	0.550 ***
ETE[27]	0.140*	0.070**	0.350***	0.120***	0.068***	0.570***

Note: Statistically significant at the 1 percent (***) and 5 percent (**) levels respectively.
Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).

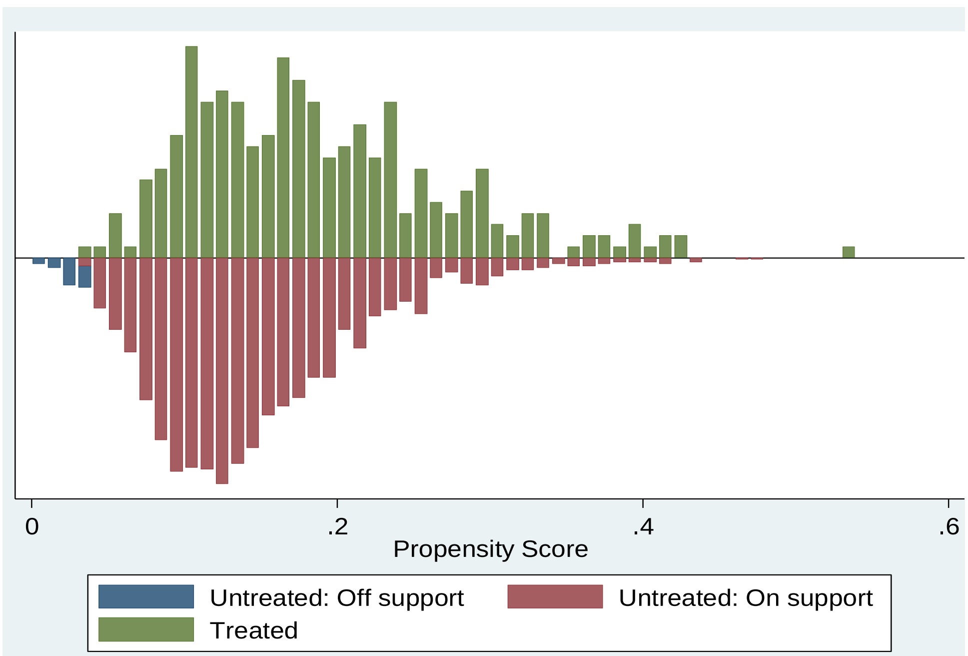

Figure 1: Propensity score distribution and common support for propensity score estimation of technology one: Spacing

[25] Ln of Consumption expenditure.
[26] Ln of child nutrition.
[27] Endogenous treatment effects with linear regression (LR) are reported.

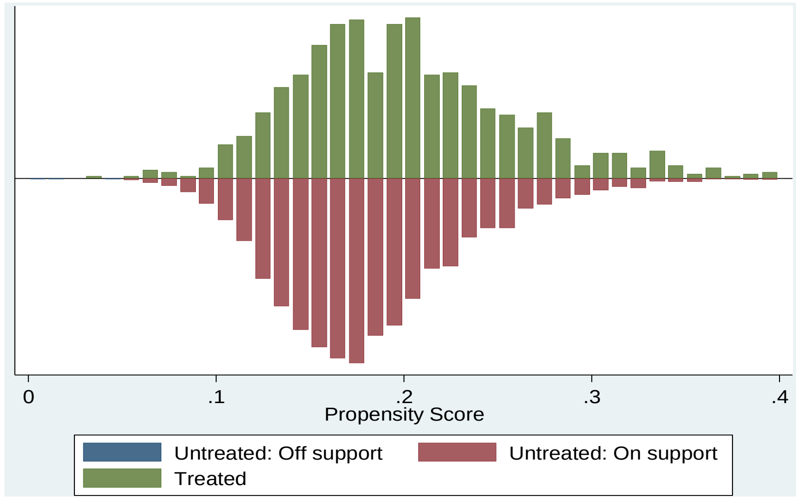

Figure 2: Propensity score distribution and common support for propensity score estimation of technology two: HYVs

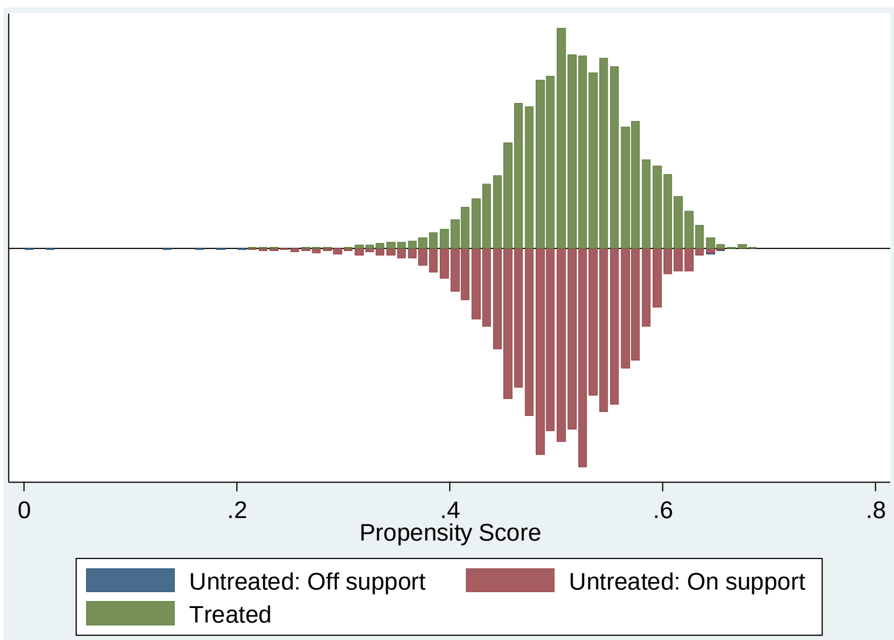

Figure 3: Propensity score distribution and common support for propensity score estimation of technology three: Fertilizers

Source: Author's calculations using WB LSMS data (2013 and 2015) (2019).[28]

[28] Untreated: on-support indicates the observations in the non-adoption group that have a suitable comparison. Untreated: off-support indicates the observations in the non-adoption group that do not have a suitable comparison.

Paper 4: Agricultural Technologies and Women's Empowerment in Rural Ethiopia: Do Improved Agricultural Technologies Matter?

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Abstract

Improved agriculture technologies are key factors for increasing welfare, especially in agriculture sector where most of the population in developing countries must deal with high workloads and little returns. Several empirical studies show that adoption of agricultural technologies can affect welfare positively in general, but because of its complex and multidimensional nature women's empowerment has not been brought to the agenda in the context of program evaluations. This study uses a panel data analysis using differences-in-differences and propensity score matching techniques. The objective of the study is evaluating the impact of adopting fertilizers with extension services on women's empowerment. The study links women's empowerment in a program evaluation setting where the issue is new to the agriculture sector. The results show that empowerment levels for both males and females are lower in Ethiopia as compared to some sub-Saharan countries. The findings also show that A-WEAI[29] is 0.50. Adopting technologies has improved empowerment in five domains (5DE), but there have been no improvements in the gender parity index (GPI). Domain-wise, income contributes most to women's disempowerment followed by lack of control over resources. The results of both propensity score matching, and differences-in-differences methods show that adoption of technologies has a positive impact on 5DE while they have mixed results for GPI. Sex-wise, the 5DE for females increases more than that for males. Finally, it is noted that a change in A-WEAI is derived more by 5DE than GPI.

Keywords: Women's empowerment; five domains; gender parity; technology adoption; Ethiopia

JEL Classification Codes: D13; I31; J16; M54; O33; Q12

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[29] Abbreviated Women's Empowerment in Agriculture Index.

1. Introduction

1.1 Background

Several studies use empowerment to represent a wide range of concepts and for describing multiple ranges of outcomes. The word has been used more often to advocate for certain types of policies and intervention strategies than for analyzing empowerment itself.

Growing concerns indicate that women's empowerment is increasingly being viewed as one of the key elements of poverty reduction strategies. It is not only seen as a development objective in itself but as a means of promoting growth, reducing poverty, and promoting better governance (King and Mason, 2001). Women's empowerment and its analyses have received a growing amount of attention in research, especially since its inclusion in the third Millennium Development Goal (MDG) of promoting gender equality and empowering women.

The third MDG is not only a goal but it also contributes to improving productivity and increasing women's efficiency (Alkire et al., 2013). Women's empowerment was a priority embedded as well in the Sustainable Development Goals (SDGs) in 2012 (United Nations, 2015): one of the 17 SDG 5 states, 'Achieve gender equality and empower all women and girls.'

Evidence also shows that women's role in agriculture is significant as they produce over 50 percent of the world's food (FAO, 2011) and comprise about 43 percent of the agricultural labor force, both globally and in developing countries (Doss, 2014). Additionally, women invest as much as 10 times more of their earnings than men do on their family's well-being in areas including child health, education, and nutrition (Duflo, 2012; Quisumbing 2003; Quisumbing and Hallman 2003; Quisumbing and Maluccio, 2000, 2003; Skoufias 2005). Women's empowerment thus has a direct impact on agricultural productivity and household food security (Harper et al., 2013; Sraboni et al., 2014), and as a result it remains at the core of agricultural research and outreach practices in developing countries (Gates, 2014). Therefore, gender related policy interventions that improve women's status and reduce gender inequalities are expected to improve women and children's well-being, owing to women's important role in childcare and managing complex household activities including being children's caretakers and preparing food.

The agriculture sector is connected to food security as it is a source of food and nutrients, a broad-based source of income, and it directly affects food prices (Arimond et al., 2010). As women account for a dominant portion of the agricultural labor force in developing countries, supporting and empowering women leads to an increase in agricultural production (FAO, 2011a). But still there are considerable gender inequalities in the agriculture sector. Poor women or women who live in poor households and those who are more vulnerable to food-insecurity are more likely to get involved in the agriculture sector particularly as wage laborers, because women's earnings are important for their families' subsistence.

The process of empowering women in the agriculture sector to produce more food for local consumption and/or local markets is one of the right ways of reducing vulnerability to poverty and food insecurity as it can help increase income generated from the sector and increase food consumption (Baiphethi and Jacobs, 2009) because women play greater roles in achieving all pillars of food security: food availability, access, utilization, and stability in their households (Bob, 2002; Galie, 2013).

Women in rural areas are producers of food, income earners, and caretakers of households and their nutrition security. Evidence shows that investments in women's empowerment related projects contributes to improving broader development outcomes including health, education, poverty reduction, reducing vulnerability to food insecurity, and economic growth (Mayoux, 2006; Quisumbing 2003; Quisumbing and Maluccio, 2000). Evidence also shows that empowering women in the agriculture sector can provide sustainable ways for them to feed themselves leading to greater income improvements from the surplus produced, which in turn makes them less vulnerable to both poverty and food insecurity.

1.2 Rationale and Motivation

In the last few decades there has been growing interest in the agriculture sector as an engine of growth and development, and parallelly a greater recognition of the important role that women play in the sector (Alkire et al., 2013; FAO, 2011a). Women in rural societies are often responsible for managing complex household activities and they also pursue multiple livelihood strategies including producing agricultural crops, tending to the animals, processing and preparing food, working for wages in agricultural or other rural enterprises, collecting fuel and water, engaging in trade and marketing, caring for family members, and looking after their homes.

Apart from recognizing women's role in agriculture, it is also important to develop indicators for measuring women's empowerment and examining its relationship with various welfare outcomes or indicators and effectively monitoring the impact of interventions in agriculture related sectors for empowering girls and women. The complex and multidimensional nature of empowerment makes its measurement more difficult, and this is especially true in the context of agriculture, where the concept is relatively new. If we fail to measure empowerment effectively, the impact of an intervention on empowerment is more likely to receive much less attention than income or other more measurable outcomes. In addition, most available indicators of women's empowerment in agriculture are not appropriate for the agriculture sector in program evaluation context.

The nature, form (characteristics), and extent of gender disparities and means of empowering women vary across countries, communities, and regions in general. In some communities, women may enjoy considerable power in some groups of indicators while they may be disempowered in others (Alkire et al., 2013). To design effective gender intervention frameworks, it is also important to recognize the context and domain specific heterogeneity in the empowerment indicators.

Nowadays the status of women in agriculture is receiving attention in literature even though a research gap exists regarding the specific impact of agriculture related technologies on empowering women. However, a large body of empirical literature has documented that adopting agricultural technologies improves social welfare besides leading to women's empowerment. As most of the indices and indicators used in monitoring programs on gender equality have little coverage of the agriculture sector and many agriculture-related indicators are gender-blind, there is a clear need for a tool to measure and monitor the impact of agricultural interventions on women's empowerment in the agriculture sector.

To the best of our knowledge, there are gaps in literature on which dimensions of women's empowerment in agriculture drive the process of empowerment/disempowerment due to the adoption of improved agricultural technologies. Therefore, the main objective of this research is identifying the impact of improved agricultural technology adoption on women's empowerment in rural Ethiopia. The study also identifies the indicators and dimensions of women's empowerment that are most affected by the adoption of the technology under study. Thus, to fill these methodological gaps and limitations in measuring women's empowerment in the agriculture sector, there is a clear need to conduct research that focuses on the adoption-empowerment linkages. We hope our new methodology will help promote further development of impact evaluation settings for studying women's empowerment in the agriculture sector.

The rest of this paper is organized as follows. Section 2 presents a literature review in the areas of technology adoption and women's empowerment while Section 3 describes the methodology used for estimating the impact of the stated technology. Sections 4, 5, and 6 discuss the findings, concluding remarks, and policy implications respectively.

2. Literature Review

2.1 A Brief Overview of Women's Empowerment

The notion and concept of empowerment is related to issues like agency, autonomy, self-direction, self-determination, liberation, participation, mobilization, and self-confidence (Ibrahim and Alkire, 2007; Narayan, 2005). There is large and growing documentation and literature on the concepts and measurements of empowerment (see Alsop and Heinsohn 2005; Alsop et al., 2006; Kabeer 1999, 2001; Narayan 2005). Most of the recent studies develop multiple indicators as empowerment is a multidimensional issue and a complex process by its very nature that can be conceived and interpreted differently by different people (for example, Malhotra et al., 2002; Mosedale, 2005).

There are many different definitions of empowerment, but most of these emphasize on agency and gaining the ability to make meaningful choices (Kabeer 2001). Many of the definitions are drawn from Sen's (1989) concept of an agent. Kabeer's 'resources, agency, and achievements' framework also provide a practical intuition for measuring empowerment, which involves three inter-related dimensions: resources (pre-conditions), agency (process), and achievements (outcomes) (Kabeer 1999, p.437). Kabeer conceived of empowerment as a process that enables individuals/groups to exercise a range of available choices.

Reflecting on the multiple experiences and views of empowerment, there are many definitions of empowerment used in literature (see Ibrahim and Alkire 2007, p.380-82 for a wide-ranging review of related works on empowerment). Three definitions of empowerment that are commonly cited are found in Alsop et al. (2006); Kabeer (2001); and Narayan (2002). Kabeer (2001, p.19) defines empowerment as "expanding people's ability to make strategic life choices, particularly in conditions where this ability had been denied to them."

Alsop et al. (2006, p. 10) describe empowerment as “a group’s or individual’s capacity to make effective choices, that is, to make choices and then to transform those choices into desired actions and outcomes.” This specific definition has two parts -- the component related to Sen’s concept of agency (the ability to act on behalf of what people value and have reason to value or make purposeful choices) and the part related to the institutional environment, which offers people the ability to exert agency fruitfully or in which actors operate on the assumption that they can influence and have the ability to transform agency into action (Alkire, 2008 ; Ibrahim and Alkire, 2007). The second component focuses on the opportunity structure that provides people what might be considered pre-conditions for effectively achieving their agency. However, these are not mutually exclusive; such that the shift is one of focus, not the only factor. It is true that the process of women’s empowerment is incomplete unless it attends to people’s abilities to act, the institutional structure, and the various non-institutional changes that are instrumental in their increased agency.

Narayan (2002, p. 14) defines empowerment as “the expansion of assets and capabilities of poor people to participate in, negotiate with, influence, control, and hold accountable institutions that affect their lives.” His definition focuses on four main elements of empowerment: access to information, inclusion and participation, accountability, and local organizational capacity. A focus on individual choices can limit the definition of empowerment, especially in cultural contexts where community and mutuality are valued. Several studies show that the definition of empowerment varies across disciplinary traditions, domains, and contexts. Most definitions of empowerment focus on issues of gaining power and control over decisions and resources that determine one’s quality of life. In their definition, both Kabeer and Alsop also include agency and capacity - the ability to act on one’s choices. In comparison, Narayan’s definition is broader than Alsop’s as it also includes the interactions between people and institutions.

When dealing with the concept of women’s empowerment, it is necessary to distinguish two aspects. First, empowerment as a field of operation, its dimensions, its inter-linkages, as well as its inter-sectionalities with other fields of power relations such as those of race/ethnicity and class (as empowerment is a multidimensional phenomenon). Second, women’s empowerment as a process in which the following elements need to be considered: awareness/ consciousness, choice/alternatives, resources, voice, agency, and participation. The second dimension of women’s empowerment is linked to enhancing their abilities to make choices in areas of their lives that matter to them, both the ‘strategic life choices’ that Kabeer (1999, 2001) discusses and choices related to their daily lives.

The existing empirical studies on ‘gender in agriculture’ consistently show that women lack access to and control over resources such as farmland and capital as well as varieties of agricultural inputs and technologies such as improved crop varieties, training, information, and marketing services (Fletschner and Kenney, 2014). Evidence also shows that women have an unmanageable workload, they lack access to credit or have no decision-making powers over credit and are poorly represented in agricultural and non-agricultural groups and organizations (Alkire et al., 2013; Akter et al., 2016b).

2.2 Adoption literature

2.3 Linkages Between Agricultural Technologies and Women's Empowerment

Very little is known about the connections between women's empowerment and the impact of improved agricultural technology adoption in rural societies. No research has systematically examined the possible relationships between farm related technologies and the participation rates and status of women and their level of empowerment relative to men, specifically in the context of the agriculture sector.

However, several studies have been conducted in the area of agricultural technology adoption and its related impact on social welfare indicators, other than empowerment. These welfare indicators include income, food security, poverty, production, employment, access to market participation, and child nutrition (Adekambi et al., 2009; Asfaw et al., 2010 ; Asfaw and Shiferaw, 2010; Asfaw et al., 2012a, 2012b; Ferede et al., 2003; Hundie and Admassie, 2016; Kassie et al., 2010; Khonje et al.,2015; Mendola,2003, 2007; Mulugeta and Hundie, 2012; Shiferaw et al., 2014; Wu et al., 2010; Zeng et al., 2014). A number of these studies evaluate the connection between causes and impacts using different estimation techniques and find that adopting modern agricultural technologies and practices improves household welfare in general.

Even if the issue of empowerment in agriculture is much less studied, due to women's remarkable role in the development process in the agriculture sector, there are several reasons to hypothesize why women's empowerment and agricultural technologies may be inter-connected. Women who are empowered tend to be more educated and have greater decision-making powers within their households. Some studies have found that women are more likely than men to invest in goods that will benefit their children and households, especially the health and education of their families (Quisumbing and Hallman, 2003; Skoufias, 2005).

Yilma et al. (2012) investigated the impact of irrigation technology adoption on empowering women in northern Ghana and found that adoption of irrigation technology positively contributed to overall poverty alleviation and empowerment of women. Their study also states that as irrigation is a labor-intensive technology, it can create employment opportunities for both the growing population and women in the agriculture sector. But the effectiveness of the technology depends on some basic factors like the operations of the input and output markets and other institutional factors such as access to credit services and provision of advisory and extension services in the sector.

Closing the gap between access and availability of technology between women and men requires that the necessary technologies exist to satisfy the priority needs of female farmers, given that women are aware of their usefulness and have the means to acquire the technologies (FAO, 2011a). If equal access to a broad range of technologies is available to women, it could help them free their time for more productive activities, enhancing their agricultural productivity, improving market returns, and empowering them to make choices that are better for themselves and their families. It has also been shown that improved crops with higher yields which are better adapted to pests and diseases can save women time spent on cropping activities. Additionally, improved practices like integrated pest management can also reduce labor requirements and costs of pesticide applications, reduce female farmers' exposure to hazardous chemicals, and increase yields.

Njuki et al. (2014) in their study in Kenya and Tanzania found that women can benefit from adoption of a technology even if they do not recognize their ownership in their households. Their study shows that in Tanzania, most adopters of irrigation pumps were men, but still women were able to use the pumps and influence decisions on how to use them like whether to irrigate the crops grown on plots they managed or not. Njuki et al. (2014) also report that the time required to fetch water for domestic and livestock uses reduced due to adoption of irrigation pumps. Again, increased incomes from the sale of irrigated farm outputs helped women make contributions to women's groups and increased their access to social capital. The study also showed that income increases enabled women to take basic personal and household decisions without consulting their husbands.

Doss (2012) in his study on women's economic empowerment in agriculture, states that improved technologies or new inputs that can save or free up women's time and improve working methods in the agriculture sector allow women to increase incomes, enable them to invest in new business ventures, lead to increased agricultural production, and help reduce their drudgery. Doss' study also argues that certain technologies that are relevant for women must be identified. Some technologies that work well for women, usually technologies that do not require much land, labor, or time must be focus areas for empowering women.

In addition, the study's results show that when available land is limited, "women can use small-scale silage-making technologies, or plastic storage tubes and boxes, to collect grasses from surrounding public lands to use as cattle feed, freeing up their own limited land to grow other vegetables. Such technologies can increase nutrition and income by both improving livestock's health and by allowing women to diversify their incomes and diets with vegetables" (Doss, 2012, p.16).

A study by Paris and Chi (2005) in Vietnam on the impact of row seeder technology on women labor, showed that the impact was based on the women's initial living status. In the case of landless and poor women who engaged in low wage paying activities and used hand-weeding practices it led to substantial income losses. Landless and poor women need to engage in off-farm activities in other villages and districts which leads to neglecting their regular tasks in their fields and the impact of row seeding becomes less.

In a study on closing the gender gap in agriculture, Huyer (2016) notes that technologies could empower women under certain circumstances including pre-conditions like correct implementation in a framework of mutually reinforcing resources, women's control over assets, equitable decision-making between women and men, and strengthened women's capacity. The study also states that technology is not sufficient in itself and it needs to be considered in the context of local knowledge, culture, gender relations, capacities, and ecosystems.

Some interventions discuss reaching women with technology without monitoring if or how this happens. Instead, identifying the distribution of rights can shed light on both the potential benefits and costs that adopting a technology confers on women and men within a household (Theis et al., 2018). This evidence will help ensure that adoption of technology strategically advances development objectives such as food and nutritional security, resilience, and women's empowerment, rather than taking technology adoption as an end in and of itself.

From this literature review it can be argued that the impact of different agricultural technologies on women's empowerment are less studied and the existing results are mixed and vary according to conditions and circumstances.

3. Methodology

3.1 Conceptual Framework of Adoption Decisions and Impact Evaluation

In the context of technology adoption, farmer households face outcomes that are uncertain (Rahm and Huffman, 1984). In such a setting, farmer households are assumed to take adoption decisions based on the motives of utility maximization.

Based on the available options (to use chemical fertilizers jointly with extension services or not) households decide to adopt a technology if it will lead to an increase in utility levels.

Following this condition, the difference between the utility from adoption (U_{1iA}) and non-adoption (U_{0iN}) of the technology is given as T* such that the utility maximizing farm household i will choose to adopt the technology if the utility gained from adopting it is greater than the utility of not adopting the technology given by($T^* = U_{1iA} - U_{0iN} > 0$). The common challenge here is that the two utilities are unobservable, so they need to be expressed as a function of observable components in the latent variable model:

$$T_{it}^* = \beta X_{it} + \varepsilon_{it}, \;\; with \;\; T_i = \begin{cases} 1 & if \; T_i^* > 0 \\ 0 & otherwise \end{cases} \qquad (1)$$

where T is a binary 0 or 1 dummy variable that indicates use of technology; T=1 if the technology is adopted and T = 0 otherwise. β is a vector of the parameters to be estimated, X is a vector that represents household characteristics, t is time (year dummies), and ε is the random error term with mean zero and constant variance.

Due to the unobservable problem of the two utilities at a time, this study uses the differences-in-differences (DID) method that can control for systematic differences between the households in the treated and control groups (Bucheli et al., 2016). The DID framework assumes that both groups, treated and control, have common pre-intervention trends. But it is less efficient when the two groups may not share similar profiles. In such cases DID fails to correctly account for heterogeneity factors. Thus, under these limitations, DID fails to produce consistent estimates.

To address this limitation, we also used the propensity score matching (PSM) technique to compare the outcomes between households with similar probabilities of being treated given a set of characteristics, X. This is a two-step procedure where we first estimated a probability model for adoption to calculate the probability (or propensity scores) of adoption for each observation. Second, we matched each adopter to a non-adopter with similar propensity score values to estimate the average treatment effect on the treated (ATT).

3.2 Measuring Women's Empowerment

Linking women's empowerment and welfare is not a straightforward task and the initial challenge starts with measuring empowerment as a variable of interest and it has linkages between women's empowerment and welfare measures which are more difficult to quantify. Several studies show that measuring women's empowerment is difficult due to the variety of definitions of empowerment.

Available literature shows that empowerment in agriculture is generally defined as one's ability to take decisions on matters related to agricultural activities as well as one's access to material and social resources needed to carry out those decisions (Alkire et al., 2013).

Women's empowerment is a multidimensional (Kabeer, 1999) and relational concept (Kabeer, 2011). Its dimensions include resources for empowerment, agency or the ability to make choices including in relation to one's gendered attitudes and beliefs; achievements in the political, economic, social and cultural realms; and the inter-generational transmission of resources and opportunities (Kabeer, 1999). Women's empowerment is contingent on social transformation across these inter-related domains (Kabeer, 2005) and it is also an individual and a collective process (Eger et al., 2018; Kabeer, 2011). Empowerment involves claims on assets and resources, as well as control over beliefs, values, and attitudes (Cornwall, 2016).

The complex and multidimensional nature of empowerment makes it difficult to measure it. This is especially true in the context of agriculture, where the concept of empowerment is relatively new (Alkire et al., 2013). Even if empowerment exists at the individual level, several existing indices of empowerment and gender are typically measured at the aggregate country level. The first and original comprehensive and more standardized approach for directly measuring women's empowerment in agriculture is the Women's Empowerment in Agriculture Index (WEAI).

WEAI is a new index used for monitoring gender gaps in agricultural production and development projects. The index consists of five domains of empowerment including women's decision-making role in agricultural production, control over income and production resources, leadership opportunities, and time availability (Alkire et al., 2013). It was originally jointly developed by USAID, IFPRI, and the Oxford Poverty and Human Development Initiative (OPHI). The index was designed as a monitoring and evaluation tool for the US government's Feed the Future initiative to directly capture the status and level of women's empowerment and inclusion levels in the agriculture sector.

WEAI uses survey level data from a self-identified primary sample of male and female adult decision makers, whose age is 18 and over in the same household which makes it easy to aggregate the index at the program level. WEAI has two sub-indices: the five domains of empowerment (5DE) and the gender parity index (GPI) that measures women's empowerment. Since its launch in February 2012, WEAI has been implemented in 19 Feed the Future focus countries (Malapit et al.,2017).

The first component of WEAI, 5DE, is constructed from individual-level empowerment scores which reflect each person's achievements in the five domains as measured by 10 indicators that show the involvement of unit i in the agriculture sector, with its corresponding weight.[30] Relative empowerment is captured by GPI, which reflects a woman's achievements in the five domains relative to the primary male in the same household.

[30] See Alkire et al. (2013) for the details of Domain, Indicator, Definition of Indicator and Weights for WEAI.

Households are classified as having gender parity if either the woman is empowered (her empowerment score is 80 percent or higher) or her score is greater than or equal to the empowerment score of the male decision maker in her household. All these indices have values ranging from 0 to 1, with higher values reflecting greater empowerment. The overall WEAI is a weighted average of 5DE and GPI, with weights 0.9 and 0.1 respectively.

WEAI builds on research to develop indicators of agency and empowerment (for example, Alsop et al., 2006; Ibrahim and Alkire 2007; Narayan 2005; Narayan and Petesch 2007) that propose domain-specific measures of empowerment obtained using questions that can be fielded in individual or household surveys.

IFPRI has released an abbreviated WEAI (A-WEAI) with six, instead of 10, indicators in the same domains (Malapit et al., 2017). A-WEAI retains the five domains and it takes about 30 percent less time to administer than the original WEAI. It also includes new autonomy vignettes, a simplified 24-hour recall time module that collects only primary activities, and streamlined sections on production decisions and resources.[31] To ensure enough coverage of relevant aspects of agriculture, it is necessary to retain all the five domains developed under WEAI so that it is possible to monitor progress and improvements in how the Feed the Future program empowers women in the agriculture sector (Alkire, 2015). Thus, the A-WEAI survey instrument reflects all five domains of empowerment in agriculture but collects only six out of the 10 original indicators. The indicators that are dropped are autonomy in production; purchase, sale, or transfer of assets; speaking in public; and leisure. Among the indicators that are retained, the definitions, cutoffs, and aggregation rules remain the same; only the indicator weights are changed (except for workload) (Malapit et al., 2017).

3.3 Model Specification

The basic assumption of DID is that there is a common trend. Even when the common trend is not violated, including additional covariates, it can increase the precision of the ATT estimation given that the model is correctly specified (Card 1992). In such a case, DID assumes the following form: a DID model with a two-ways fixed effect:

$$y_{it} = \alpha_i + \varepsilon_t + \theta T_{it} + \mu_{it} \quad (2)$$

where y_{it} is the outcome variable (5DE and empowerment gap (EG) in our case) for household i in the adoption category at time t, T is the treatment indicator factor which equals 1 if the household is an adopter and 0 otherwise. α_i are individual fixed effects, ε_t are the year or wave fixed effects, and μ_{it} is the random error term. One possible way of relaxing the common-trend assumption is by adding further covariates to the DID regression model. This nature (feature) is a significant advantage of DID compared to other program evaluation methods. Even when the common-trend holds, including additional covariates (either time-

[31] A comparison of the domains and indicators in the original WEAI and A-WEAI is presented in detail in the Appendix.

invariant or unit (individual) specific) it helps increase the precision of the estimated impacts. In such cases we have the following DID form:

(3) $$y_{it} = \alpha_i + \varepsilon_t + \theta T_{it} + \beta X_{it} + \mu_{it}$$

where X_{it} is a vector of other covariates.

An additional generalization of the DID estimator is required when T_{it} changes over time across different individuals or locations. This is a generalization of the two-time DID to multiple-time cases (Angrist and Pischke, 2008), and in such a case we need to use regression with lags and leads of the treatment variable T_{it}. Correcting for possible differences in time trends across different individuals or locations/regions is necessary for DID to remain unbiased, and we estimate the following modified version of DID:

(4) $$y_{it} = \alpha_i + \varepsilon_t + \sum_{\tau=0}^{m} T_{t-\tau}\,\theta_{-\tau} + \sum_{\tau=0}^{q} T_{t+\tau}\,\theta_{+\tau} + \beta X_{it} + \mu_{it}$$

where *m* shows the number of lags ($\theta_{-1}, \theta_{-2}, \ldots, \theta_{-m}$) or post-treatment effects and *q* shows the number of leads ($\theta_{+1}, \theta_{+2}, \ldots, \theta_{+q}$) or anticipatory effects. Note, however, that we need relatively longer periods of panel data to estimate a model of this form. Unfortunately, we cannot apply this method in the current study because of the limited rounds of the panel data we used.

The second method is PSM which compares the outcomes of a treated observation with the outcomes of comparable non-treated observations. It is defined as the conditional probability of receiving a treatment given pre-treatment characteristics as:

(5) $$P(X) \equiv Pr\{T_i = 1|X\} = E\{T_i|X\}$$

where T_i= {0, 1} is the indicator of exposure to treatment and X is the multidimensional vector of pre-treatment characteristics.

Rosenbaum and Rubin (1983) show that if the exposure to treatment is random within cells defined by X, it is also random within cells defined by the values of the variable $P(X)$. Let Y_{1t} be the value of the welfare outcome variable when household *i* is subject to treatment ($T = 1$) and Y_{0t} be the same variable when the household does not adopt the technology ($T = 0$). So, given a population of units denoted by i, if the propensity score $P(X_i)$ is known ATT can be estimated as:

(6) $$\begin{aligned} ATT &= E\{Y_{1t} - Y_{0t}|T = 1\} \\ &= E(Y_{1t}|T = 1) - E(Y_{0t}|T = 1) \end{aligned}$$

For robustness of our results we used the balance of the scores and covariates using the following methods: As suggested by Rosenbaum and Rubin (1985) the standardized bias (SB) between treatment and non-treatment samples is suitable for quantifying the bias between both the groups. For each variable and propensity score, the standardized bias is computed before and after matching as:

(7) $$SB(X) = 100 \frac{\bar{X}_t - \bar{X}_{nt}}{\sqrt{\frac{V_t(X) + V_{nt}(X)}{2}}}$$

where $\bar{X}_t \, and \, \bar{X}_{nt}$ are the sample means for the treatment and control groups, and $V_t(X) \, and \, V_{nt}(X)$ are the corresponding variances. The bias reduction (BR) can also be computed as:

(8) $$BR = 100\left(1 - \frac{B(X)_{after}}{B(X)_{before}}\right)$$

where $B(X)$ is the proportion difference in the outcomes of the treatment and control groups. There are many important theoretical reasons (and huge empirical literature supporting the theories) why agricultural technologies can improve farm households' well-being, but how can we be sure that the better well-being of adopters compared to non-adopters is because of technology adoption (or not)? In other words, the differences between the treated and control groups could be because of the pre-treatment differences, or agricultural technology adoption may also lead to welfare deterioration. Several existing studies conclude that improved agricultural technologies act in favor of the adopters. But it should also be noted that adoption may worsen social welfare.

3.4 Modeling the Women's Empowerment in Agriculture Index (WEAI)

In measuring empowerment, the weights of the 5DE and GPI sub-indices are 90 percent and 10 percent respectively. However, the choice of weights for the two sub-indices is somewhat subjective and open to changes but focuses more on 5DE while still recognizing the importance of gender equality. This study uses A-WEAI that retains the five domains of empowerment, but the 10 indicators of WEAI are reduced to six.

The construction of WEAI is based on the Alkire-Foster (AF) (2007, 2011a) methodology which focuses on building multidimensional poverty. The measure uses a 'dual-cut-off' to identify and count poor people and aggregates based on an extension of the Foster-Greer-Thorbecke (FGT) measures to multidimensional space (Alkire et al., 2013). The AF methodology is used as it not only creates the indices, but it also enables us to put the headline figure into its individual indicators.

i) The 5DE index

The 5DE index assesses if women are empowered and the degree to which they are empowered across the five domains in agriculture. The 5DE sub-index captures women's empowerment within their households and communities and the women who are disempowered. It also shows the percentage of domains in which they meet the required thresholds and thus experience adequacy.

Even if the end objective is measuring empowerment, 5DE is constructed in such a way that disempowerment can also be analyzed, which allows us to identify the critical indicators that must be addressed for increasing women's empowerment. This is a crucial contribution for decision makers that they should focus on the most disempowered. Following Alkire et al. (2013) the disempowerment index across the five domains (M_0) was first computed and then 5DE was computed as $(1 - M_0)$.

ii) Identification of the disempowered

In the identification stage, there are two equivalent notations that can be used for describing the construction of 5DE. The first is the 'positive' notation that focuses on the percentage of empowered women and adequacies among the disempowered ones. The second notation focuses on the percentage of women who are disempowered and the percentage of domains in which they face inadequate achievements. In this study, we use the second notation which is consistent and applicable with the M_0 measurement of multidimensional poverty (Alkire and Foster, 2011a, 2011b).

To make the identification process of disempowerment simple, we first need to code all the adequacy indicators. All adequacy indicators need to be coded so that they assume the value 1 if the individual is inadequate in that indicator and 0 otherwise.

Let us consider a sample of N individuals and let $D \geq 2$ be the number of domains and $x = [x_{ij}]$ be the N×D matrix of inadequacy achievements, where x_{ij} is the achievement of individual i (i = 1, ..., N) in domain j (j = 1, ..., D). Then x has the following form:

$$x = \begin{bmatrix} x_{11} & . & x_{1j} & . & x_{1D} \\ . & . & . & . & . \\ x_{i1} & . & x_{ij} & . & x_{iD} \\ . & . & . & . & . \\ x_{N1} & . & x_{Nj} & . & x_{ND} \end{bmatrix}$$

Let$|z_j| > 0$ be the 1xD vector, $z = (z_1, \dots, z_D)$, containing the inadequacy cut-offs of the D dimensions; this is used for determining if a person is inadequate in each of the D dimensions. In this case it should be noted that each row vector x_i is the individual i's achievements in each dimension, and x_j is a column vector of dimension j achievements across the set of individuals. For the purpose of our analysis under this part, we assume that for an indicator j and individual i the inadequacy occurs when x_{ij} falls strictly below the respective cut-off, that is, $x_{ij} < z_j$.

Given the weights for each domain, a matrix of inadequacy achievement $\tilde{x}^0 = [\tilde{x}^0_{ij}]$ is derived from x as: $\forall\ i\ and\ j$:

(9) $$\tilde{x}^0_{ij} = \begin{cases} 1 & if\ x_{ij} < z_j \\ 0 & otherwise \end{cases}$$

This implies that if $\tilde{x}^0_{ij}$= 1 it means that individual i is inadequate in dimension j and $\tilde{x}^0_{ij}$= 0 otherwise. A horizontal summation of each row of $\tilde{x}^0$gives us a column vector c of the inadequacy count containing c_i, the number of inadequacies suffered by individual i.

An inadequacy score c_i is computed for each person according to his or her inadequacies across all indicators. The inadequacy score of each person is calculated by summing the weighted inadequacies experienced so that the inadequacy score for each person lies between 0 and 1. The score reaches its maximum of 1 when the person experiences inadequacy in all the 6 indicators. A person who has no inadequacy in any indicator receives a c_i score equal to 0. This can be given more formally in the following sections.

The weighted inadequacy score c_i, is ($w_j \tilde{x}_{ij}^0$) for each indicator, finding the aggregate inadequacy score for each individual (c_i) is constructed as the horizontal sum of the weighted inadequacy score for each individual given as:

$$(10) \qquad c_i = \sum_{j=1}^{D} w_j \, \tilde{x}_{ij}^0$$
$$= w_1 \tilde{x}_{1i}^0 + w_2 \tilde{x}_{2i}^0 + \cdots w_D \tilde{x}_{Di}^0$$

where $\tilde{x}_{Di}^0 = 1$ if person i has an inadequate achievement in indicator D and $\tilde{x}_{Di}^0 = 0$ otherwise and w_D is the weight attached to indicator i with $\sum_{d=1}^{D} w_D = 1$.

As Alkire et al. (2013) state, a second cut-off or threshold is used for identifying the disempowered portion of the population. This threshold, the disempowerment cut-off, is the share of (weighted) inadequacies that a woman must have to be considered disempowered, and it is denoted by k. Unlike the Alkire and Foster (2011a, 2011b) approach we do not censor the inadequacies of the empowered for those whose inadequacy score is less than or equal to the disempowerment cut-off.[32]

iii) Computing 5DE

First, we compute the five domains of the disempowerment index (M_0) following Alkire and Foster's (2011a, 2011b) method and structure of the adjusted headcount measure, M_0 that combines two key pieces of information: first the proportion or incidence of individuals (within a given population) whose share of weighted inadequacies is more than the disempowerment cut-off, k and second, the intensity of their inadequacies, the average proportion of (weighted) inadequacies that they experience.

More formally, the first component is called the disempowered headcount ratio (H_p) and is given by:

$$H_p = \frac{q}{N}$$

Here q is the number of individuals who are disempowered, and N is the total population.

The second element of 5DE is called the intensity (or breadth) of disempowerment (A_p). It is the average inadequacy score of disempowered individuals in the population and can be expressed as:

$$\boldsymbol{A_p = \frac{\sum_{i=1}^{N} c_i}{q}}$$

where $\boldsymbol{c_i}$ is the inadequacy score of individual i, N is the total population, and q is the number of disempowered individuals.

[32] As discussed in Alkire et al. (2013, p.34), "For those whose inadequacy score is less than or equal to the disempowerment cut-off, even if it is not 0, their score is replaced by 0, and any existing inadequacies are not considered in the censored headcounts." This important step is referred to as censoring the inadequacies of the empowered (Alkire and Foster, 2011a, 2011b; Alkire et al., 2011). To differentiate the original inadequacy score from the censored one, the notation $c_i(k)$ is used for the censored inadequacy score. Note that when $c_i > k$, then $c_i(k) = c_i$, but if $c_i \leq k$, then $c_i(k) = 0$ in the censored inadequacy score.

Once we have computed the disempowered headcount ratio and intensity of disempowerment, we need to find M_0. M_0 is the product of H_p and A_p . Finally, the 5DE is easily computed from M_0:

$$M_0 = H_p \times A_p$$

$$5DE = 1 - M_0 \tag{11}$$

The sensitivity of the empowerment classification for different cut-offs and the selected disempowerment cut-off is 20 percent (Alkire et al., 2013). This definition of the disempowerment cut-off implies that an individual is disempowered if his/her inadequacy score is greater than 20 percent. This is like saying that an individual is identified as empowered in 5DE if he/she has adequate achievements in four of the five domains and enjoys adequacy in some combination of the weighted indicators that sum up to 80 percent or more.

iv) Breaking down M_0 by domains and indicators

Once we have computed 5DE and M_0 following the Alkire et al. (2013) method, M_0 can be decomposed into its different domains and indicators following the approach developed by Alkire and Foster, (2011a, 2011b) and Alkire and Santos (2013, 2014). One of the most important features of M_0 is that once the disempowered have been identified (M_0 has been computed), it can easily be decomposed into its component or indicators to reveal how people are disempowered across those components, the composition by indicator of the inadequacies that they experience, and so on.

To decompose M_0 by indicators, we need to compute the disempowered headcount ratio in each indicator. The headcount ratio for a particular indicator is the number of disempowered people who are inadequate in that indicator divided by the total population. After all the headcount ratios have been computed, it can be verified that the weighted sum of the headcount ratios also generates the population's M_0. That is, if M_0 is constructed from all 6 indicators, then the decomposition becomes:

$$M_{0_{Population}} = \sum_{d=1}^{D} w_i \, H_i \tag{12}$$
$$= w_1 H_1 + w_2 H_2 + \cdots + w_6 H_6$$

where w_i is the weight of indicator i and H_i is the headcount ratio of indicator i.

The percentage contribution of each domain to overall disempowerment is computed as: Percentage contribution of domain D to $M_0 = \frac{w_D H_D}{M_{0_{Populatiom}}} \times 100$

The contributions of all domains will add up to 100 percent. Alkire et al. (2013, p.78) state that, "whenever the contribution to disempowerment of a certain indicator greatly exceeds its weight, this suggests that the disempowered are more inadequate in this indicator than in others. Such indicators with high inadequacy point to areas for intervention to increase empowerment."

v) Decomposing M_0 by population sub-groups

The main decomposing factors in this study are region and gender of the sample households. The second key feature of M_0 (and of 5DE) is that it can be decomposed by population sub-groups such as regions, sex, ethnic groups, or other categories, depending on the sample design. For instance, in our study we have included all the nine rural regions in the country in which the data from the survey is representative; the formula for regional decomposition is given as:

(13) $$M_{0_{country}} = \frac{N_1}{N} \times M_{0_1} + \frac{N_2}{N} \times M_{0_2} + \cdots + \frac{N_9}{N} \times M_{0_9}$$

where N_1 denotes region one, N_2 denotes region two and so on, $\frac{N_1}{N}$ is the population share of region one to the total population, and similar to others implying that $N_1 + N_2 + \cdots + N_9$ $=N$. This relationship can be extended for any number of groups (such as for sex and ethnic groups) if their respective populations add up to the total population.

The contribution of each group to overall disempowerment can also be computed using the formula:

Contribution of region one to $M_{0_{country}} = \frac{\frac{N_1}{N} \times M_{0_1}}{M_{0_{country}}} \times 100$

The same method can be followed to compute the contribution of the remaining regions. When a region or some group's contribution to disempowerment widely exceeds its population share, this a good indicator that some regions or groups may bear an unequal share of poverty in the country. This also calls for relevant and appropriate policy interventions in these regions.

vi) The Gender Parity Index (GPI)

WEAI's GPI sub-index is a measure of intra-household inequalities. In one way, it measures the relative parity (equality) in 5DE scores of the women and men indices in the same household and in another way it accounts for the gap in empowerment between men and women for households in which there is no gender parity (Gupta et al., 2017). Like 5DE, GPI is computed on the basis of how people experience gender parity in a positive sense; however, its construction also facilitates an analysis of households that lack gender parity directly (Alkire et al., 2013).

We calculate the male inadequacy scores in the same way as the female inadequacy scores. For the purpose of establishing gender parity, the score for women whose inadequacy score is less than or equal to the disempowerment threshold of k is replaced by 0 even if the value is not zero, and we use the notation $c_i(k)$for the new censored inadequacy score. Note that when $c_i > k$, then $c_i(k) = c_i$, but if $c_i \leq k$, then $c_i(k) = 0$. This censoring of the inadequacy score enables us to easily identify a change in the empowerment gap (EG) among women who lack parity with primary men in their households.

Each dual-adult household is classified as having or lacking gender parity. Households lack parity if the female is disempowered and her censored inadequacy score is higher than the censored inadequacy score of her male counterpart (Alkire et al., 2013).

GPI provides two streams of important information about women's empowerment: (1) the percentage of women who lack gender parity relative to their male household counterparts, and (2) the extent of the inequality in empowerment between those women who lack parity and the men with whom they live.

The first component corresponds to the proportion of gender parity–inadequate households (H_{GPI}):

$$H_{GPI} = \frac{h}{m}$$

where h is the number of households classified as lacking gender parity and m is the total number of dual-adult households in the population.

The second component is called average empowerment and it provides information about the average percentage gap between the censored inadequacy scores for women and men living in households that lack gender parity (I_{GPI}), and is given as:

$$I_{GPI} = \frac{1}{h}\sum_{j=1}^{h}\frac{c_j(k)^M - c_j(k)^W}{1 - c_j(k)^M}$$

where $c_j(k)^W$ and $c_j(k)^M$ are the censored inadequacy scores of the primary women and men respectively living in household j, and h is the number of households that are gender parity inadequate.

GPI is computed as:

$$GPI = 1 - (H_{GPI} \times I_{GPI}) \quad (14)$$

As is evident, GPI is equivalent to one minus a 'poverty gap' or P_1 measure of the Foster–Greer–Thorbecke family of poverty measures (1984), and GPI is likewise decomposable by sub-groups. It is also parallel in structure to 5DE, both being one minus a poverty-gap type of measure. The GPI score can be improved by increasing the percentage of women who enjoy gender parity (reducing H_{GPI}) or, for those women who are less empowered than men, by reducing the empowerment gap between the males and females in the same household (reducing I_{GPI}).

3.5 Data and a description of the Variables

This analysis is based on panel data obtained from the World Bank's Living Standard Measurement Survey-Integrated Surveys on Agriculture (LSMS-ISA): Ethiopia Socioeconomic Survey (ESS)-Waves 1-3. The data targeted the rural parts and small and medium towns in Ethiopia, but households from both small and medium towns were excluded because of non-applicability of agricultural technology adoption. The survey data has good qualities like it covers different household members including males and females in the same household. We restrict the sample to rural households to ensure that women's A-WEAI indicators among urban households that are not engaged in agricultural production are not misinterpreted as low empowerment achievements.

The original WEAI includes 5 domains and the indicator, but this study uses A-WEAI which still retains the 5 domains of empowerment, but WEAI's 10 indicators are reduced to 6. To measure disempowerment scores, we first identified the inadequacy achievements of each person on the five domains (production, resources, income, leadership, and time). Next, we calculated inadequacy scores for each person by taking a weighted sum of the inadequacies experienced.

We included households that had dual-adult households (primary adult male and female pairs in the same household). To ensure this pairing, households without a primary adult male and female pair were excluded from the sample. In several cases, the primary and secondary male and female were husband and wife; however, men and women can be classified as the primary male and female decision makers regardless of their relationship to each other. Finally, we obtained 3,382 (1,691 females and males) for each wave giving us a sample of 10,146 individuals. In this study, agricultural technology refers to joint application of recommended amounts of chemical fertilizers with extension services.

4. Empirical Results

4.1 Results of the Descriptive Analyses

Agricultural technology in this study refers to joint application of a recommended amount of chemical fertilizers per plot with extension services. So, adopters are farm households who use the recommended amount of fertilizers per plot with extension services, while non-adopters are those who do not use both in combination.

Even if the objective of the current study is identifying the impact of improved agricultural technology adoption on women's empowerment in rural parts of Ethiopia, the 5DE was constructed in such a way that disempowerment can be analyzed at different levels which enables us to identify which dimensions of women's empowerment drive the process of empowerment/disempowerment. The advantage of this construction is that it allows us to identify the critical indicators of the most disempowered which must be a focus area for improving women's empowerment. So, here the computation of a disempowerment index across the five domains (M_0) is done as the first step and then 5DE is computed as (1- M_0).

For comparison purposes, we present M_0 and its decomposition also for the sample of men. Decomposition was also done for both males and females based on their adoption status. To identify the areas that contribute most to women's disempowerment, we decomposed the women's disempowerment index (M_0) by domain and indicator. Table 1 gives the summary of empowerment levels and adoption status for the whole sample categorized by sex. The results show that women's empowerment is almost similar to that of men's in general, but non-adopter men have relatively more empowerment scores than women. A simple description of the inadequacy scores also shows that about 8.73 percent of the women and 9.68 percent of the men in the sample were empowered.

Concerning empowerment by adoption status, farmers who adopted the specified technology were more empowered as compared to the non-adopters. The result shows that about 14 percent of the adopters were empowered as compared to 8.43 percent empowerment level for the non-adopters. In Table 2 we can see that the adopters achieved higher adequacy scores (47.72 percent in the six indicators), as compared to non-adopters (44.66 percent). This result shows that there are significant differences in 5DE scores between the two technology adoption groups.

[Insert Table 1 about here]

[Insert Table 2 about here]

Another comparison is given in Table 3 on women's empowerment and gender parity by women's status of technology adoption. Gender parity is enjoyed by 58.80 percent of the women, which implies that about 41.20 percent of the women lack gender parity with the primary males in their households. In each category, about 67.42 percent of the adopters and 57.31 percent of the non-adopters enjoyed parity in their households. Women in the adopter group were significantly more empowered in 5DE and enjoyed more gender parity as compared to women in the non-adopter group. This implies that about 14.51 percent and 7 percent women in the adopter and non-adopter group respectively, enjoyed empowerment in both 5DE and gender parity. More women were found under the category in which parity is enjoyed, but with no empowerment in 5DE. About 52.95 percent of the women the who adopted technology and 50.31 percent who did not enjoyed gender parity, but they were disempowered. The results also show that about 32.12 percent adopters and 42.02 percent non-adopters lacked empowerment and parity with the males in their households.

[Insert Table 3 about here]

The results of the sample A-WEAI score and its components are reported in Table 4, and it shows a sample achievement score of 0.46. in 5DE and 0.91in GPI score. The average empowerment gap of the 41.20 percent women who were less empowered than the primary males in their households is 22.3 percent that leads to the overall GPI of 0.91 (1 – [41.20 percent x 22.3 percent]).

Table 5 gives descriptions of inadequacy scores and the contribution of each domain/ indicator. The results show that the domains that contributed the most to women's disempowerment are control overuse of income (27.90 percent) and lack of control over resources (23.80 percent). Three-fourth of the women in the study were not empowered and lacked access to credit and the ability to take sole or joint decisions about it and control over use of income. In Table 5 we can also see that more than 60 percent of the women are not yet empowered and lack control over assets and about 52 percent women are not yet empowered and lack decision making in agricultural production. Similarly, about 43 percent of the women are not empowered and are not group members or do not belong to any group in their community, and about 37 percent are overburdened with work and have inadequate time allocated for doing this work. When we further decompose the results into adopter females and non-adopter females, the former achieves better in more indicators.

When it comes to the contribution of each indicator to women's disempowerment, women were the most disempowered in control over use of income indicator (27.90 percent) followed by decision making in productive inputs (19.10 percent). On the other hand, women were less disempowered in access to and decisions on credit (9.40 percent).

A comparison of men's inadequacies in empowerment with those of women shows that it is the same for both. Lack of control over use of income and group membership in the community contributed more to men's disempowerment than to women's disempowerment. On the other hand, men's results show relatively little disempowerment in workload overburden and in decision making on agricultural production as compared to women. These results are also supported by different figures drawn for different disaggregated portions of the population (by sex, adoption groups, and regions, see Figures 1-6 in the Appendix).

[Insert Table 4 about here]

[Insert Table 5 about here]

4.2 Econometric Results

One more step before the estimation of causal effects was the balancing test and passing different quality checking tests**.** After estimating the propensity scores for the adopter and non-adopter groups, the common support conditions were checked. The covariate balancing tests before and after matching are reported in Table B3 in the Appendix. The standardized mean difference in the overall covariates used in the propensity score for the three technologies (around 15 percent before matching) reduced to around 2 percent after matching. The pseudo R^2 also dropped significantly from around 9-12 percent before matching to about 0.3-1.17 percent after matching. The likelihood ratio test was also statistically significant before matching under all the outcomes but became insignificant after matching. The low pseudo R^2, high bias reduction, and the insignificant p-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score was successful in terms of balancing the distribution of covariates between the two groups.

After computing the propensity scores, we estimated the ATT of the outcome variables, namely 5DE and GPI using PSM and DID with fixed effects for different samples (for pooled, females, and males) separately. Following the PSM approach we used four matching algorithms -- nearest neighborhood matching (NNM), kernel matching (KM), radius matching (RM), and stratified matching (SM). A separate model was estimated for 5DE, its components, and GPI under each approach.

The estimated results based on PSM using the whole sample are reported in Table 6. The results show that the adoption of a recommended amount of chemical fertilizers with extension services had a positive and significant effect on 5DE across all matching algorithms. The estimated impact ranged from 4.3 to 6.1 percent and it was statistically significant. This result implies that estimated average differences in the five domains of empowerment for similar pairs of household members (females and males in each household) who have different technological status is significantly different. The results also show that the adopters were better-off due to the technology as compared to the non-adopters such that adopters got more empowered in 5DE and their empowerment score increased on average by about 5 percent.

[Insert Table 6 about here]

Table 7 gives the estimated impact of technology adoption on each sex separately; the results show that adoption affected empowerment positively and significantly for both the sexes. In the case of females, the empowerment score in 5DE increased from 5.6 to 8.3 percentage points while the increase in 5DE for males was in the range of 2.9- 4.9 percent. On average, the proportion of adopter women and men empowered in each of the five domains of A-WEAI is closer to each other. Adopter females and males had almost similar empowerment scores in 5DE which is about 48 percent as the outcome mean shows.

Unlike women in the adopter households, women in the non-adopter households had a lower empowerment score in 5DE than non-adopter men. This suggests that even if they do not adopt the technology non-adopter men are more empowered as compared to non-adopter women. On average, disempowerment in the five domains of agriculture is more severe in the non-adopter female group. In other words, women would have benefited more from adopting the technology as compared to men. This result supports the real condition of most developing countries, especially in the agriculture sector, where men usually enjoy more empowerment than women. Thus, interventions will affect more women and girls who face more burdens in the sector than men.

[Insert Table 7 about here]

Next the impact of technology adoption on each domain and the contribution of each domain to women's empowerment in 5DE was computed, and the results are reported in Table 8. The findings support the results in Table 5 in general. The domain that contributed the most to women's empowerment is time use. Its estimated impact ranged from 3.2 to 4.2 percent increase in the empowerment score measured by 5DE. The second domain that contributed the most to women's empowerment is resource control and use. On average, adoption led to a 1.5 percent increase in the total empowerment score through ownership of assets and access to and decisions on credit use.

When it comes to the domain-wise impact, we observe that adoption was not associated with a statistically significant change in decisions on production, except for radius and stratification matching. Unlike 5DE's other domains, the coefficient estimate for leadership was negative and statistically significant. This means that the empowerment of women who adopted the technology went down through the leadership component. A possible reason for this could be that as women participate in their community and take positions, they will spend less time on their fields and take lesser time to deal with the technology.

[Insert Table 8 about here]

The last estimation of PSM gives the impact of the technology adopted on the empowerment gap (EG)[33] or gender disparities (Table 9. The ATT term is negative in all the matching methods and statistically significant. The result suggests that EG declined for adopter women compared to non-adopter households. EG for adopter women declined between 2.0-2.98 percent. These results remain consistent with different matching algorithms and suggest that there is a negative effect of being an adopter of the specified technology on EG, which means technology adoption leads to a reduction in gender disparities between men and women in the same household. Looking more closely at the issue we also considered the impact of the specific technology on women who lacked parity with the primary males in their households and the results are reported in Table 10. Unlike the estimation of the model for all the females, this time the results show that adoption was not associated with a statistically significant change in EG, but it still supports the earlier results in sign that all are negatively related to adoption, except for NNM with five neighbors.

[Insert Table 9 about here]

[Insert Table 10 about here]

[33] Reflects the relative empowerment gap between female and male scores in the 5DE.

Next, we estimated the impact using DID following the fixed effects approach. Table 11 gives the DID results for three different models -- pooled sample, females, and males --- separately. The findings show that adoption of chemical fertilizers with extension services increased 5DE for adopters under all the three models (see Columns 2 to 4 in Table 11). In the entire sample, technology increased empowerment scores in the five domains by about 4.30 percent. This result tells us that adoption led to a 4.30 percent increase in 5DE scores if an individual adopted a technology, irrespective of sex. Concerning the second model, the results show that adoption led to a 4.80 percent increase in empowerment for women who used the specified technology as measured by the 5DE score. Similarly, adopter males also benefitted from the technology as their empowerment score increased by about 3.90 percent, but the impact was less than that for female adopters which is contrary to our expectations.

After including other controls our results are almost similar under all the models. However, while computing the impact of the technology on each component of 5DE using DID, our results were different from what we obtained under PSM (see Table 12), except for the time dimension. We found that adoption was not statistically significant for any of the first four components. The exception was time allocation where adoption led to a 3.50 percent increase in empowerment. This finding shows that time use domain still drives the change in 5DE, as we see in the PSM results in Table 8. The other exception for the time use dimension of 5DE was that none of the control variables included in the model affected it, while they did affect the first four components.

[Insert Table 11 about here]

[Insert Table 12 about here]

Contrary to PSM's results concerning the impact of technology on EG, the results are mixed following the DID approach. Technology adoption leads to a reduction in EG under the first three models in Table 13 when all women are included. For example, in Model 1 when we only include the treatment status of households and observation periods, the results show that adoption is associated with a 1.20 percent decline in EG for all the women. In Model 2 we estimated the impact by adding personal and household characteristics, but the result is still negative though it is not statistically significant implying that adoption led to narrowing the empowerment gap even if the impact was not powerful enough. In Model 3 we added other controls and the findings support the results of the first two models in sign.

However, when only women who lack gender parity are considered, the result has the opposite sign, where adoption leads to an increase in the empowerment gap, but it is not statistically insignificant (see Model 4 in Table 13). These mixed results make the impact of technology adoption on EG inconclusive following the DID approach. However, since our interest is seeing the impact on women who lack parity, it is possible to argue that adoption does not help women reduce the empowerment gap with the primary males in their households. This implies that improved agricultural technologies do not necessarily affect the empowerment gap.

[Insert Table 13 about here]

A further disaggregation was done based on major regions in the country and the results are presented in Table 14. Disaggregating A-WEAI by components can help identify key areas of empowerment/disempowerment (for men as well as women), which can be used for prioritizing interventions. Our disaggregation of the index helped us identify regional variations to see the achievements and consider the status of empowerment conditions between primary males and females in these regions. We estimated the technology impact on 5DE and its components for both pool sample and women only.

Based on the results of the regional disaggregation we can see that adoption did not improve women's empowerment in all the regions. The impact was more in regions like Amhara and Oromia. In Amhara region adoption increased the 5DE by 14.30 percent and 15.50 percent for the whole sample and women respectively. Similarly, in Oromia the technology impact was significant which led to an increase in 5DE by 12.90 percent and 15 percent for the whole sample and women respectively. These results support the real situation in the country that the two regions are dominant in all economic indicators; the most arable land and productive resources are found in these regions. New and improved agricultural technologies are also used widely in these two regions.

We also found that the impact of technology adoption was negative and significant in regions like Benishangul and SNNP. Even if available literature has come to the conclusion that modern agricultural technologies improve welfare, it should also be noted that they may also worsen social welfare. In our case adoption led to a decline in 5DE in some regions. However, the aggregate impact was positive and significant indicating that technology has the power to improve empowerment in 5DE. The results are almost similar to the components of 5DE across regions, with a few exceptions.

Finally, we compared the impact of the technology on 5DE and EG computed using DID and PSM (Table 15). The results show that there were almost similar impacts under both approaches in magnitude as well as in signs, except in a few cases.

[Insert Table 14 about here]

[Insert Table 15 about here]

To conclude, the process of change in A-WEAI is derived by 5DE so that technology adoption affects 5DE more than GPI as both the PSM and DID results show. These results also show that the driving force behind changes in A-WEAI is women's empowerment in the five domains rather than the issue of gender parity.

5. Conclusion

So far, very few studies have measured women's empowerment in agriculture and incorporated this in program evaluation settings. Its complex and multidimensional nature has made these attempts difficult in the areas of empowerment and gender parity/disparity. However, evidence shows that the important role that women play in the agriculture sector is growing both in terms of their participation and contribution to the sector which implies that women's empowerment plays a big role in welfare improvements such as increase in food security, reduction in poverty, and increase in agriculture production and consumption.

To fill this gap and contribute to existing literature, the current study evaluated the impact of adopting recommended amounts of chemical fertilizers with extension services on women's empowerment. For estimation purposes, we used DID with fixed-effects and PSM methods.

Prior to the formal estimation of the technology's impact on empowerment, we looked at each domain and the components of A-WEAI briefly. Here we were interested in seeing women's disempowerment and gender disparities which are relevant for policy interventions. The results showed that women's disempowerment was almost similar to that of men. About 91.27 percent of women and 90.32 percent of men were disempowered in A-WEAI's five domains. The sample achievement score in 5DE was 0.46 while GPI was 0.91 which implies that the sample A-WEAI is 0.50. Gender parity was enjoyed by 58.80 percent of the women, which implies that about 41.20 percent of the women did not enjoy gender parity with the primary males in their households and the average empowerment gap (EG) of women who lacked parity was 22.30 percent.

About 67.42 percent of the adopters and 57.31 percent of the non-adopters enjoyed parity in their households. Women in the adopter group were significantly more empowered in 5DE and enjoyed more gender parity as compared to women in the non-adopter group. When we look at the contribution of each domain to disempowerment, the results show that women were the most disempowered in the income domain (27.90 percent) followed by lack of control over resources (23.80 percent) and providing inputs for production decisions (19.10 percent).

In the empirical section, the estimation results from our study under both the methods showed that adoption of the specified agricultural technology had a robust, significant, and positive impact on the 5DE components of A-WEAI while the results are mixed for GPI. Our results are also consistent across estimation methods, except in a few cases and the magnitude of the estimated effects is closer to each other under both the estimation methods. Using the PSM method, we found that adoption led to a 4.3 to 6.1 percent increase in 5DE. Sex-wise, 5DE for females increased from 5.6 to 8.3 percent while for men it increased from 2.9 to 4.9 percent. Looking at the impact of technology adoption on each domain, we found that the domain that contributed the most to women's empowerment was time use, which increased in the range 3.2 to 4.2 percent. The second domain that contributed the most to women's empowerment was resource control and use where the increase was about 1.5 percent. Last, using PSM, we estimated the impact of the technology on the empowerment gap for all women, and we found that EG for adopter women declined between 2.0 and 2.98 percent. But, when we considered only women who lacked parity with the primary males in their households, the result showed that adoption did not affect EG, but it still had a negative sign.

Almost similar results were obtained using DID with a fixed effects approach. We estimated three different models, for the whole sample, for females, and for males separately, and the findings for the whole sample showed that technology increased the empowerment score by about 4.30 percent, while for the females group adoption led to a 4.80 percent increase in their empowerment and for the male group it led to 3.90 percent increase in empowerment. In computing the impact of the technology on each component of 5DE, adoption did not affect any of the first four components, except time allocation where adoption led to a 3.50 percent increase in empowerment. The results for the impact of technology on EG were mixed following the DID approach. Technology adoption led to a reduction in EG when all women were included, but when only women who lacked gender parity were considered adoption led to an increase in the empowerment gap, but it was statistically insignificant. This implies that the improved agricultural technology did not necessarily affect the empowerment gap. Thus, program interventions in relation to agriculture technologies and gender parity need to be context or country specific when extrapolating results from a specific location to other areas for policy guidelines.

Finally, a regional disaggregation of the impact showed that adoption did not improve women's empowerment in all the regions. The impact was more powerful in regions like Amhara and Oromia while it was negative and significant in regions like Benishangul and SNNP. However, the aggregate impact was positive and significant indicating that technology had the power of improving empowerment in 5DE. Last, we observed that the change in A-WEAI was derived by 5DE rather than by GPI.

6. Policy implications

Since women's empowerment is a relatively new concept in the agriculture sector and this study is the first attempt to study this in a program evaluation setting(context), it highlights some potential areas that need important policy interventions to enable farm households to exploit the full benefits of improved agricultural technologies.

On the basis of our results there is a positive and significant impact of improved agricultural technologies on 5DE, while at the same time we observed that there is a weak association between the impact of adoption and GPI.

Even though we found a strong impact of adoption on 5DE, the value of this component of A-WEAI (5DE) is by far lower than other developing countries, for example, Uganda's 5DE is 0.83 (Malapit et al., 2015, p. 24) while in our case 5DE for Ethiopia is only about 0.46. Similarly, A-WEAI is also lower, with a value of 0.500, compared again to Uganda's score of 0.84. This needs policy interventions that increase A-WEAI and its sub-indices, especially 5DE.

The strong relationship between the impact of adoption and 5DE levels in our study suggests that empowerment of women could be a pathway for reducing poverty and vulnerability to food insecurity. It was, however, observed that more that 75 percent of the women did not have access to credit or did not take sole or joint decisions. A significant number of women did not have control over the use of income generated or owned by their household members. Policy support is needed for improving access to and methods of using credit in households and for ensuring that women have the ability to take decisions related to incomes. It is also important to note that provision and access to improved inputs like fertilizers and support extension services also need to be improved.

Another finding of our study is that there was no difference in the empowerment gap between adopter and non-adopter females. Adoption did not help adopter females to narrow down the existing empowerment gap with the primary males in their households. One possible reason for this is that men and women are able to take decisions to differing degrees in the same households. Hence, awareness generation about joint decisions and cooperation on issues in their households will increase the impact of the technology on the existing gender gap.

In Ethiopia, social norms are important determinants of participation in economic and social activities. Accounting for social norms or practices that possibly up-grade/limit women's participation need to be an important component of policies and strategies in shaping access to opportunities such as healthcare, education, and employment. This will also help women take decisions within the established gender roles if they are provided with skills and knowledge improvements through awareness creation about gender equity and its importance for social welfare across contexts.

References

Adekambi, S. A., Diagne, A., Simtowe, F., & Biaou, G. (2009). The Impact of Agricultural Technology Adoption on Poverty: The Case of, NERICA Rice Varieties in Benin. Contributed paper prepared for presentation at the International Association of Agricultural Economists' conference, Beijing, China, August 16-22, 2009.

Akter, S., Krupnik, T. J., Rossi, F., & Khanam, F. (2016b). The influence of gender and product design on farmers' preferences for weather-indexed crop insurance. *Global Environmental Change*, 38, 217–229.

Alkire, S. (2008). Concepts of measures and agency. In K. Basu, & R. Kanbur (Eds.). Arguments for a better world: Essays in honor of Amartya Sen. Vol. 1, ethics, welfare and measurement. Oxford, UK: Oxford University Press, pp. 455–474.

Alkire, S. (2015). Report on the Women's Empowerment in Agriculture Index. Unpublished report prepared by the Oxford Poverty and Human Development Initiative for IFPRI. Oxford, UK.

Alkire, S., & Foster, J. (2007). Counting and Multidimensional Poverty Measurement. OPHI Working Paper 7, Oxford University.

Alkire, S., & Foster, J. (2011a). Counting and Multidimensional Poverty Measurement. *Journal of Public Economics*, 95(7–8), 476–487.

Alkire, S., & Foster, J. (2011b). Understandings and Misunderstandings of Multidimensional Poverty Measurement. *Journal of Economic Inequality*, 9(2), 289–314.

Alkire, S., & Santos, M.E. (2013). A Multidimensional Approach: Poverty Measurement and Beyond. *Social Indicators Research*, 112(2), 239-257.

Alkire, S., & Santos, M.E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development*, 59, 251–274.

Alkire, S., Meinzen-Dick, R.S., Peterman, A., Quisumbing, A.R., Seymour, G., & Vaz, A. (2013). The Women's Empowerment in Agriculture Index. *World Development*, 52, 71–91.

Alsop, R., & Heinsohn, N. (2005). *Measuring empowerment in practice: Structuring analysis and framing indicators*. World Bank Policy Research Working Paper No. 3510.

Alsop, R., Bertelsen, M., & Holland, J. (2005). *Empowerment in practice: From analysis to implementation*. The World Bank.

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton, NJ: Princeton university press.

Arimond, M., Hawkes, C., Ruel, M. T., Sifri, Z., Berti, P. R. & Leroy, J. L. (2010). "Agricultural interventions and nutrition: Lessons from the past and new evidence", in B. Thompson, and L. Amoroso (eds), *Combating micronutrient deficiencies: Food-based approaches*. Rome: FAOU and CAB International, pp. 41–75.

Asfaw, S., & Shiferaw, B. (2010). Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Poster presented at the 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19 – 23, 2010

Asfaw, S., Kassie, M., Simtowe, F., & Leslie, L. (2012b). Poverty Reduction Effects of Agricultural Technology: A Micro-evidence from Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Asfaw, S., Shiferaw, B., & Simtowe, F. (2010). Does technology adoption promote commercialization? Evidence from chickpea technologies in Ethiopia. In *CSAE 2010 conference on Economic Development in Africa, University of Oxford, UK*.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012a). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295.

Baiphethi, M. N., & Jacobs, P. J. (2009). The contribution of subsistence farming to food security in South Africa. *Agrekon*, 48, 459–482.

Bob, U. (2002). Rural African women, food (in) security and agricultural production in the Ekuthuleni land redistribution project, KwaZulu-Natal. *Agenda*, *17*(51), 16-32.

Bucheli, J. R., Bohara, A. K., & Villa, K. (2016). *The Impact of a Rural Road Development Project on Multidimensional Poverty in Nepal*. Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, and July 31-August 2.

Card, D. (1992). Using regional variation in wages to measure the effects of the federal minimum wage. *Industrial and Labor Relations Review*, *46*(1), 22-37.

Cornwall, A. (2016). Women's empowerment: What works? *Journal of International Development*, *28*(3), 342-359.

Doss, C. (2014). "If women hold up half the sky, how much of the world's food do they produce?", in A.R. Quisumbing, R. Meinzen-Dick, T.L. Raney, A. Croppenstedt, J.A. Behrman, and A. Peterman (eds), *Gender in Agriculture* **(pp. 69-88)**. The Netherlands: Springer.

Doss, C. R., Bockius-Suwyn, Z., & D'Souza, S. (2012). *Women's Economic Empowerment in Agriculture: Supporting women farmers*. Washington, DC: UN Foundation.

Duflo, E. (2012). Women empowerment and economic development. *Journal of Economic Literature*, *50*(4), 1051-79.

Eger, C., Miller, G., & Scarles, C. (2018). Gender and capacity building: A multilayered study of empowerment. *World Development*, 106, 207–219.

FAO (Food and Agriculture Organization of the United Nations) (2011a). *The state of food and agriculture 2010–2011. Women in agriculture: Closing the gender gap for development.* Rome: Food and Agriculture Organization of the United Nations.

Ferede, S., Ayele, G., & Teklewold, H. (2003). Impact of Technology on Households Food Security, in Tef and Wheat Farming Systems of Moretna_Jiruworeda. Ethiopian Agricultural Research Organization (EARO), Research Report No.48.

Fletschner, D., & Kenney, L. (2014**).** "Rural women's access to financial services: credit, savings, and insurance", in A.R. Quisumbing, R. Meinzen-Dick, T.L. Raney, A. Croppenstedt, J.A. Behrman, and A. Peterman (eds), *Gender in **Agriculture*** (pp. 187-208)**.** The Netherlands: Springer.

Foster, J., Greer, J., & Thorbecke, E. (1984). A Class of Decomposable Poverty Measures. *Econometrica,* 52(3), 761-766.

Galie, A. (2013). Empowering women farmers. The case of participatory plant breeding in ten Syrian households, *Frontiers: A Journal of Women Studies*, 34(1), 58–92.

Gates, M.F. (2014). Putting women and girls at the center of development. *Science***,** 345, 1273–1275.

Gupta, S., Pingali, P.L., & Pinstrup-Andersen, P. (2017). Women's empowerment in Indian agriculture: does market orientation of farming systems matter? *Food security*, 9(6), 1447–1463.

Harper, S., Zeller, D., Hauzer, M., Pauly, D., & Sumaila, U.R. (2013). Women and fisheries: Contribution to food security and local economies. *Marine Policy*, 39, 56–63.

Hundie, B., & Admassie, A. (2016). "Potential Impacts of Yield-Increasing Crop Technologies on Productivity and Poverty in two Districts of Ethiopia", in F. Gatzweiler and J. von Braun (eds), *Technological and Institutional Innovations for Marginalized Smallholders in Agricultural Development.* Springer International Publishing (pp. 397-421).

Huyer, S. (2016) Closing the Gender Gap in Agriculture. *Gender, Technology and Development* 20(2), 105–116.

Ibrahim, S., & Alkire, S. (2007) Agency and Empowerment: A Proposal for Internationally Comparable Indicators. *Oxford Development Studies*, 35 (4), 379–403.

Kabeer, N. (1999). Resources, agency, achievements: Reflections on the measurement of women's empowerment. *Development and Change*, 30, 435–464.

Kabeer, N. (2001). *Reflections on the measurement of women's empowerment–theory and practice, Discussing Women's Empowerment—Theory and Practice.* Stockholm: Novum Grafiska AB.

Kabeer, N. (2005). Gender equality and women's empowerment: A critical analysis of the third millennium development goal 1. *Gender & Development*, 13(1), 13–24.

Kabeer, N. (2011). Between affiliation and autonomy: Navigating pathways of women's empowerment and gender justice in rural Bangladesh. *Development and Change*, 42(2), 499–528.

Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda. *Environment for Development Discussion Paper-Resources for the Future (RFF)*, (10-11).

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, 66, 695–706.

King, E., & Mason, A. (2001). *Engendering development: Through gender equality in rights, resources, and voice*. The World Bank.

Malapit, H. J., Pinkstaff, C., Sproule, K., Kovarik, C., Quisumbing, A. R., & Meinzen-Dick, R. S. (2017). *The Abbreviated Women's Empowerment in Agriculture Index (A-WEAI).* IFPRI Discussion Paper 1647. Washington, DC.

Malapit, H., Kovarik, C., Sproule, K., Meinzen-Dick, R., & Quisumbing, A. R. (2015). Instructional guide on the abbreviated women's empowerment in agriculture index (A-WEAI). *Washington, DC: International Food Policy Research Institute*.

Malhotra, A., Schuler, S. R., & Boender, C. (2002, June). Measuring women's empowerment as a variable in international development. In *background paper prepared for the World Bank Workshop on Poverty and Gender: New Perspectives* (Vol. 28).

Mayoux, L. (2006). Sustainable Micro-Finance for Women's Empowerment, A Report of the International Mutual Learning Workshop, September 4–8, Chennai, India.

Mendola, M. (2003). Agricultural technology and poverty reduction: A micro-level analysis of causal effects. *Centro Studi Luca D'Agliano Development Studies Working Paper*, (179), November, University of Milan-Bicocca, Italy.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy, 32*(3), 372–393.

Mosedale, S. (2005). Assessing women's empowerment: towards a conceptual framework. *Journal of international development*, *17*(2), 243-257.

Mulugeta, T., & Hundie, B. (2012). Impacts of Adoption of Improved Wheat Technologies on Households' Food Consumption in Southeastern Ethiopia. Selected Poster prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, August 18-24, 2012.

Narayan, D. (2002). *Empowerment and Poverty Reduction*. Washington, DC: The World Bank.

Narayan, D., & Petesch, P. (2007). *Moving Out of Poverty: Cross-Disciplinary Perspectives on Mobility*. Washington, DC: The World Bank.

Narayan-Parker, D. (2005). *Measuring Empowerment: Cross-Disciplinary Perspectives.* Washington, DC: The World Bank.

Njuki, J., Waithanji, E., Sakwa, B., Kariuki, J., Mukewa, E., & Ngige, J. (2014). A qualitative assessment of gender and irrigation technology in Kenya and Tanzania. *Gender, Technology and Development, 18*(3), 303-340.

Paris, T.R., & Chi, T. T. N. (2005). The impact of row seeder technology on women labor: A case study in the Mekong Delta, Vietnam. *Gender, Technology and Development*, *9*(2), 157-187.

Quisumbing, A. R. (ed.) (2003). *Household Decisions, Gender, and Development: A Synthesis of Recent Research*. Washington, DC: IFPRI.

Quisumbing, A. R., & Maluccio, J.A. (2003). Resources at Marriage and Intrahousehold Allocation: Evidence from Bangladesh, Ethiopia, Indonesia, and South Africa. *Oxford Bulletin of Economics and Statistics,* 65 (3), 283–327.

Quisumbing, A.R., & Hallman, K. (2003). Marriage in Transition: Evidence on Age, Education, and Assets from Six Developing Countries. *Policy Research Division Working Paper 183. Population Council*.

Quisumbing, A.R., & Maluccio, J. A. (2000). *Intrahousehold Allocation and Gender Relations: New Empirical Evidence from Four Developing Countries*. Washington, DC: IFPRI.

Rahm, M. R., & Huffman, W.E. (1984). The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. *American Journal of Agricultural Economics,* 66 (4), 405–413.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica*, *70*(1), 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, *39*(1), 33-38.

Sen, A. (1989). Cooperation, inequality, and the family. Population and Development Review, 15, 61–76.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy,* 44, 272-284.

Skoufias, E. (2005). *PROGRESA and Its Impacts on the Welfare of Rural Households in Mexico. Research Report 139.* Washington, DC: IFPRI.

Sraboni, E., Malapit, H. J., Quisumbing, A. R., & Ahmed, A. U. (2014). Women's empowerment in agriculture: What role for food security in Bangladesh? *World Development*, 61, 11–52.

Theis, S., Lefore, N., Meinzen-Dick, R., & Bryan, E. (2018). What happens after technology adoption? Gendered aspects of small-scale irrigation technologies in Ethiopia, Ghana, and Tanzania. *Agriculture and Human Values*, *35*(3), 671-684.

United Nations (2015). *Transforming our world: The 2030 Agenda for Sustainable Development.* New York: United Nations.

Wu, H., Ding, S., Pandey, S., & Tao, D. (2010). Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching analysis in rural China. *Asian Economic Journal*, *24*(2), 141-160.

Yilma, T., Berg, E., & Berger, T. (2012). Empowering African Women through Agricultural Technologies: The Case of Irrigation Technology in Northern Ghana. Integrating Governance and Modeling project.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2014). Agricultural Technology Adoption and Child Nutrition: Improved Maize Varieties in Rural Ethiopia. Selected Paper prepared for presentation at the Agricultural and Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Appendix

Appendix-A: Estimation output Tables

Table 1: Empowerment and Adoption status by sex

Sex	Adoption status		Enjoy Empowerment		
	Adopter	Non-Adopter	Adopter	Non-Adopter	Total
Male	701	4372	13 %	9.19 %	9.68%
Female	744	4329	14.92 %	7.67 %	8.73 %
Total	1445	8701	13.96 %	8.43 %	

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 2: Adequacy achievements in the 5DE by Adoption status and sex

Sex	Adoption status		
	Adopter	Non-Adopter	Total
Male	46.97 %	45.04 %	45.31 %
Female	48.42 %	44.27 %	44.87 %
Total	47.72 %	44.66 %	

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 3: Women's empowerment and Gender Parity by Adoption status

Adoption Status	Enjoy parity	Enjoy Both	Parity, but not empowered	No parity, but empowered	Lack both
Adopter	67.42%	14.51 %	52.95 %	0.43 %	32.12 %
Non-adopter	57.31 %	7.00 %	50.31 %	0.67 %	42.02 %
Total	58.80%				

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 4. Results of Sample A-WEAI Scores with its Components

Indexes	Total Sample	
	Women	Men
Disempowered headcount (H)	94.00 %	93.70 %
Average inadequacy score (A)	58.20 %	57.84 %
Disempowerment Index (M_0)	0.547	0.542
5DE Index (1- M_0)	0.453	0.458
Number of observations	5073	5073
Percentage of women with no gender parity (H_{GPI})	41.2 %	
Average Empowerment Gap (I_{GPI})	22.3 %	
Gender Parity Index (GPI)	0.908	
A-WEAI score (0.9 x 5DE + 0.1 x GPI)	0.500	

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 5: Summary of Inadequacy scores and contribution of each indicator

Statistics	Production	Resources		Income	Leadership	Time
	Input in productive decisions	Ownership of assets	Access to and decisions on credit	Control over use of income	Group membership	Workload
Indicator weight	0.20	0.13	0.07	0.20	0.20	0.20
Women (All)						
% Headcount	52.20%	63.00%	78.06%	76.35%	42.64%	37.35%
% Contribution	19.10%	14.40%	9.40%	27.90%	15.6%	13.60%
% Contribution by dimension	19.10%	23.80%		27.90%	15.60%	13.60%
Women (Adopter)						
% Headcount	47.85%	58.33%	74.46%	72.85%	50.94%	23.39%
% Contribution	18.70%	14.40%	9.20%	28.50%	19.90%	9.20%
% Contribution by dimension	18.70%	23.60%		28.50%	19.90%	9.20%
Women (Non-Adopter)						
% Headcount	52.59%	63.78%	78.68%	76.95%	41.21%	39.76%
% Contribution	19.10%	14.40%	9.40%	27.90%	15.6%	13.60%
% Contribution by dimension	19.10%	23.80%		27.90%	15.60%	13.60%
Men						
% Headcount	51.03%	62.53%	77.92%	77.92%	43.00%	36.49%
% Contribution	18.80%	14.40%	9.40%	28.30%	15.70%	13.50%
% Contribution by dimension	18.80%	23.80%		28.30%	15.70%	13.50%

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 6: Impact of technology adoption on 5DE (Pooled sample)

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNMa[34]	0.480	0.428	0.052(5.97) ***
NNMb[35]	0.480	0.431	0.048(4.60) ***
RM	0.480	0.418	0.061(5.83) ***
KMa[36]	0.480	0.432	0.047(5.79) ***
KMb[37]	0.480	0.436	0.043(5.34) ***
SM[38]	0.480	0.424	0.056(11.47) ***

Note: Statistically significant at the 1 % (***) probability level.
Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 7: Impact of technology adoption on 5DE by Sex

Matching Type	Outcome mean and ATT					
	Female			Male		
	Adopters	Non-adopters	ATT	Adopters	Non-adopters	ATT
NNMa	0.487	0.425	0.062(5.05) ***	0.472	0.431	0.041(3.34) ***
NNMb	0.487	0.405	0.082(5.55) ***	0.472	0.433	0.039(2.59) **
RM	0.488	0.405	0.083(5.67) ***	0.478	0.440	0.038(2.48) **
KMa	0.487	0.431	0.056(4.90) ***	0.472	0.443	0.029(2.55) **
KMb	0.487	0.427	0.060(5.51) ***	0.472	0.438	0.034(2.95) ***
SM	0.487	0.425	0.062(7.36) ***	0.472	0.422	0.049(6.53) ***

Note: Statistically significant at the 1 % (***) and 5 % (**) probability levels respectively.
Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

[34] NNM based on five neighbors and common support.
[35] NNM based on a single neighbor and common support.
[36] Kernel-based matching with a band width of 0.06 and common support.
[37] Kernel-based matching with a band width of 0.03 and common support.
[38] Stratification matching based on the survey year.

Table 8: PSM Results of the Impact of technology adoption on each Domain of 5DE

ATT by Domain					
Matching Type	Production	Resources	Income	Leadership	Time
NNMa	0.004(0.85)	0.016(4.51) ***	0.014(3.17) ***	-0.007(1.38)	0.035(7.94) ***
RM	0.012(1.90) *	0.021(5.00) ***	0.013(2.49) **	-0.006(0.95)	0.042(7.22) ***
KMa	0.002(0.50)	0.013(4.27) ***	0.012(3.19) ***	-0.008(1.90) *	0.036(8.99) ***
KMb	0.002(0.47)	0.014(4.32) ***	0.014(3.42) ***	-0.007(1.53) *	0.037(8.96) ***
SM	0.013(3.16) ***	0.013(4.62) ***	0.005(2.22) **	-0.000(0.18)	0.032(9.69) ***

Note: Statistically significant at the 1 % (***), 5 % (**), and 10 % (*) probability levels respectively.

Absolute values of t-statistics in parenthesis.

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 9: Impact of technology adoption on the Empowerment Gap (EG), All Female, n=5,073

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNMa	0.063	0.084	-0.020(3.30) ***
NNMb	0.063	0.091	-0.028(3.41) ***
RM	0.062	0.092	-0.030(3.58) ***
KMa	0.063	0.088	-0.025(4.36) ***
KMb	0.063	0.087	-0.023(4.12) ***
SM	0.063	0.088	-0.025(4.46) ***

Note: Statistically significant at the 1 % (***) probability level.

Absolute values of t-statistics in parenthesis.

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 10: Impact of technology adoption on the Empowerment Gap (EG), for Females without parity, n=2,090

Matching Type	Outcome mean		ATT
	Adopters	Non-adopters	
NNMa	0.208	0.206	0.004(0.13)
NNMb	0.208	0.221	-0.013(0.92)
RM	0.209	0.222	-0.013(0.98)
KMa	0.208	0.209	-0.001(0.11)
KMb	0.209	0.211	-0.002(0.17)
SM	0.208	0.213	-0.005(0.53)

Note: Absolute values of t-statistics in parenthesis.

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 11: DID results Adoption: Outcome variable is 5DE

Variable	Model 1: Total Sample	Model 2: Female	Model 3: Male
Treatment	0.043(6.35) ***	0.048(5.06) ***	0.039(3.94) ***
Year dummy			
2013_Dummy	0.295(67.82) ***	0.296(48.28) ***	0.294(47.50) ***
2015_Dummy		0.358(45.64) ***	0.364(45.90) ***
Religion dummy	0.361(64.86) ***		
Protestant_dummy	-0.060(3.17) ***	-0.053(2.00) ***	-0.066(2.47) **
Tradition_dummy	-0.079(2.81) **	-0.084(2.07) **	-0.076(1.91) *
Pagan_dummy		0.055(1.29)	0.039(0.95)
Marital_stat_dummy			
Married_dummy	0.019(1.37)	0.007(0.36)	0.029(1.57)
Single_dummy	0.014(0.47)	0.002(0.04)	0.026(0.62)
Separeted_dummy	0.139(2.33) **	0.117(1.49)	0.167(1.82) *
Crop_rotation	0.034(5.97) ***	0.037(4.57) ***	0.031(3.86) ***
House_rooms	0.005(1.53)	0.007(1.51)	0.003(0.69)
Kitchen_type	-0.010(1.51)	-0.008(0.99)	-0.010(1.16)
Family_size_AE	0.001(2.41) **	0.006(1.61) *	0.007(1.80) *
Mother's Educ	0.030(2.19) **	0.026(1.40)	0.034(1.68) *
Light_source	0.008(1.23)	0.007(0.81)	0.009(0.95)
Age	0.004(3.03) ***	0.005(2.24) ***	0.004(2.05) **
Age^2	-0.000(2.88) **	-0.000(2.22) **	-0.000(1.86) *
Constant	0.175 (7.69) ***	0.171(5.35) ***	0.181 (5.57) ***
Observation	8,914	4,455	4,459
No. of Groups	3,382	1,691	1,691

Note: Statistically significant at the 1 % (***), 5 % (**), and 10 % (*) probability levels respectively.
Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 12: DID Results of the Impact of technology adoption on each Domain of 5DE

Variable	Production	Resources	Income	Leadership	Time
Treatment	0.005(1.01)	0.003(0.99)	0.002(0.60)	0.004(1.01)	0.035(6.63) ***
Year dummy					
2013_Dummy	0.089(22.80) ***	0.025(11.37) ***	0.049(8.21) ***	0.169(74.29) ***	-0.002(0.70)
2015_Dummy	0.002(0.53)	0.054(19.56) ***	0.163(71.72) ***	0.134(47.18) ***	0.003(0.74)
Religion dummy					
Tradition_dummy	-0.034(1.63)	-0.013(0.91)	-0.013(1.10)	0.007(0.44)	-0.012(0.57)
Crop_rotation	0.012(2.89) ***	-0.000(0.02)	0.010(3.86) ***	0.017(5.53) ***	0.002(0.42)
Family_size_AE	0.005(2.45) **	0.003(2.32) **	0.000(0.81)	-0.002(1.39)	0.000(0.02)
Mother's Educ	-0.008(0.85)	0.002(0.26)	-0.001(1.49)	0.020(3.13) ***	0.013(1.31)
Age	0.002(1.82) *	0.001(0.75)	0.000(0.49)	0.000(0.39)	0.001(1.21)
Age^2	-0.000(1.87) *	-0.000(0.41)	-0.000(0.29)	-0.000(0.19)	-0.000(1.60)
Constant	0.285(30.15) ***	0.804(44.94) ***	0.786(53.44) ***	0.794(43.32) ***	0.899(33.07) ***

Observation	4,458	4,458	4,458	4,458	4,458
No. of Groups	1,691	1,691	1,691	1,691	1,691

Note: Statistically significant at the 1 % (***), 5 % (**), and 10 % (*) probability levels respectively.
Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 13: DID results Adoption: Outcome variable is EG

Variable	Model 1	Model 2	Model 3	Model 4(Female without parity)
Treatment	-0.012(1.67) *	-0.010(1.37)	-0.017(2.27) **	0.029(1.54)
Year dummy				
2013_Dummy	0.005(1.02)	0.005(1.11)	0.007(1.45)	0.018(1.65)
2015_Dummy	0.033(6.98) ***	0.036(7.08) ***	0.021(3.23) ***	0.042(3.02) ***
Religion dummy				
Protestant_dummy		0.019(0.93)	-0.054(1.61)	-0.007(0.15)
Pagan_dummy		-0.030(0.89)	0.025(1.21)	-0.001(0.02)
Family_size_AE		-0.003(0.99)	-0.002(0.49)	0.004(0.60)
Mother's Educ		-0.001(0.45)	-0.008(0.62)	-0.010(0.33)
Age		-0.003(1.80) *	-0.004(2.35) **	-0.001(0.16)
Age^2		0.0001.57)	0.000(2.00) **	0.000(0.01)
Crop_rotation			0.010(1.45)	0.026(1.98) *
Cooking_fuel			-0.064(2.16) **	-0.120(1.72) *
Light_source			-0.013(1.88) *	-0.019(1.23)
Water_source			0.010(1.25)	0.005(0.37)
Toilet_type			0.009(1.84) *	0.003(0.30)
Constant	0.081)22.22) ***	0.156(4.30) ***	0.159(4.11) ***	0.153(1.88) *
Observation	5,073	5,029	4,458	1,763
No. of Groups	1,691	1,691	1,691	1,213

Note: Statistically significant at the 1 % (***), 5 % (**), and 10 % (*) probability levels respectively.
Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 14: Decomposition of the technology impact on 5DE and each component by Regions

Region	ATT					
	5DE	Production	Resources	Income	Leadership	Time
Tigray_A[39]	0.021(1.27)	0.021(2.71) **	0.006(1.14)	-0.018(3.17) ***	-0.018(2.37) **	0.030(4.21) ***
Tigray_B[40]	0.029(1.18)	0.024(2.12) **	0.007(0.94)	-0.018(2.16) **	-0.012(1.11)	0.027(2.69) **
Amhara_A	0.143(12.05) ***	0.012(2.24) **	0.021(5.58) ***	0.038(7.38) ***	0.042(8.89) ***	0.030(6.57) ***
Amhara-B_	0.155(9.66) ***	0.012(1.58)	0.024(4.65) ***	0.043(6.03) ***	0.046(7.12) ***	0.031(5.02) ***
Oromiya_A	0.129(6.51) ***	0.040(5.40) ***	0.021(3.56) ***	0.012(1.73) *	0.010(1.26)	0.046(7.71) ***
Oromiya_B	0.150(5.34) ***	0.038(3.59) ***	0.027(3.27) ***	0.024(2.29) **	0.007(0.64)	0.053(6.97) ***
Benishan_A	-0.155(4.35) ***	-0.066(6.19) ***	0.005(0.39)	-0.044(4.16) ***	-0.086(6.48) ***	0.036(2.85) **
Benishan_B	-0.155(3.09) ***	-0.075(6.14) ***	0.008(0.50)	-0.033(1.95) *	-0.086(4.50) ***	0.031(1.63)
SNNP_A	-0.102(7.88) ***	-0.009(1.70)	-0.009(2.37) **	-0.023(5.76) ***	-0.075(15.48) ***	0.014(2.86) **
SNNP_B	-0.098(5.37) ***	-0.012(1.55)	-0.007(1.24)	-0.021(3.60) ***	-0.075(10.94) ***	0.016(2.27) **
Harari_A	-0.001(0.037)	-0.007(0.58)	0.004(0.52)	-0.004(0.38)	0.029(2.47) **	0.035(3.25) ***
Harari_B	0.005(0.11)	-0.011(0.68)	0.011(0.99)	0.001(0.08)	-0.036(2.19) **	0.039(2.67) **

Note: Statistically significant at the 1 % (***), 5 % (**), and 10 % (*) probability levels respectively.
Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

Table 15: Comparisons of the Impact Using DID and PSM Results on 5DE and EG

Estimation method		Outcome variables			
		5DE: Total Sample	5DE: Female	EG (All Female)	EG (Female without parity)
DID		0.043(6.35) ***	0.048(5.05) ***	-0.017(2.27) **	0.028(1.48)
PSM	NNMa	0.052(5.97) ***	0.062(5.05) ***	-0.020(3.30) ***	0.004(0.13)
	RM	0.061(5.83) ***	0.083(5.67) ***	-0.030(3.58) ***	-0.013(0.98)
	KMa	0.047(5.79) ***	0.056(4.90) ***	-0.025(4.36) ***	-0.001(0.11)
	KMb	0.043(5.34) ***	0.060(5.51) ***	-0.023(4.12) ***	-0.002(0.17)
	SM	0.056(11.47) ***	0.062(5.05) ***	-0.025(4.46) ***	-0.005(0.53)

[39] Region name followed by "A" is the result for the whole sample.
[40] Region name followed by "B" is the result for the women only.

Note: Statistically significant at the 1 % (***), 5 % (**), and 10 % (*) probability levels respectively. Absolute values of t-statistics in parenthesis.
Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

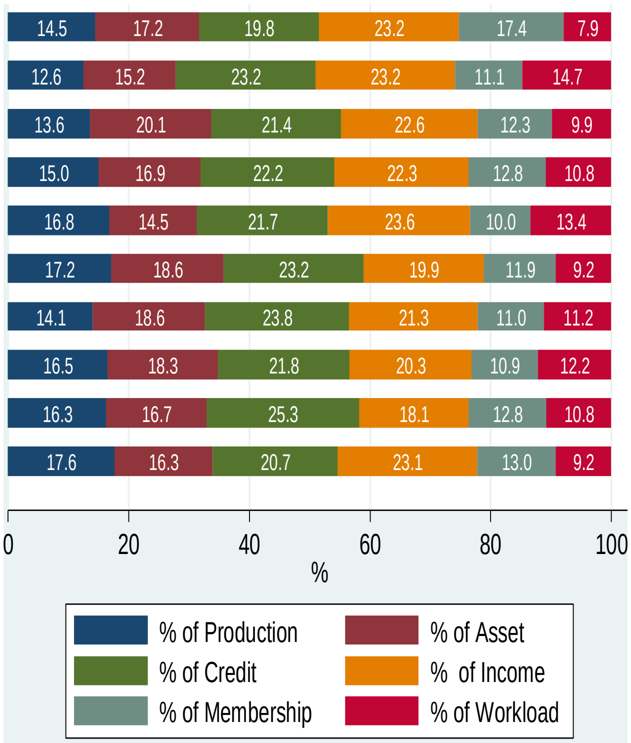

Figure 1: Contribution of each indicator to inadequacy by region

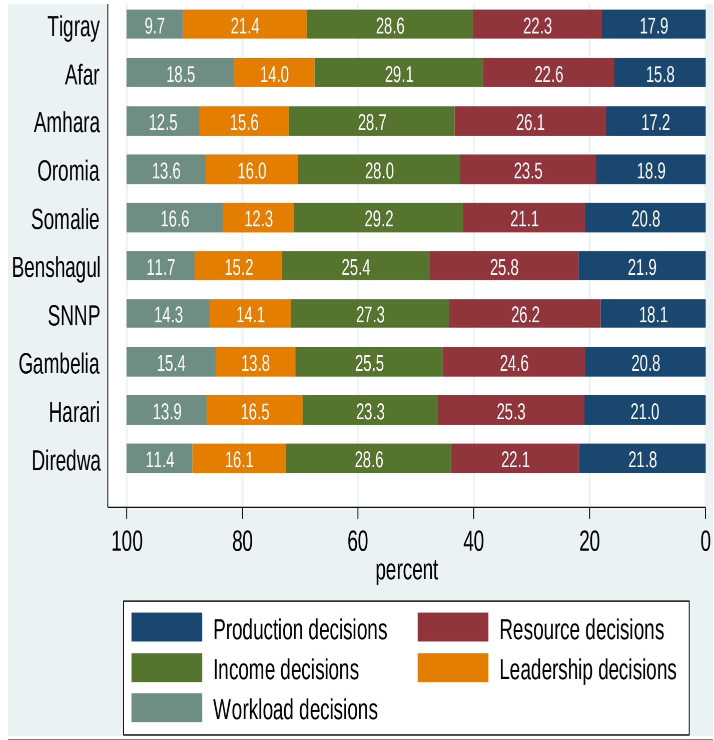

Figure 2: Contribution of each of the five domains to disempowerment by region

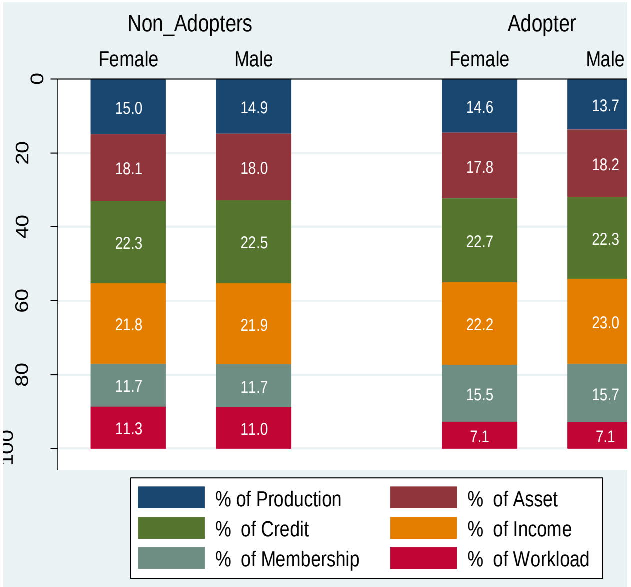

Figure 3: Contribution of each indicators to inadequacy by sex and adoption status

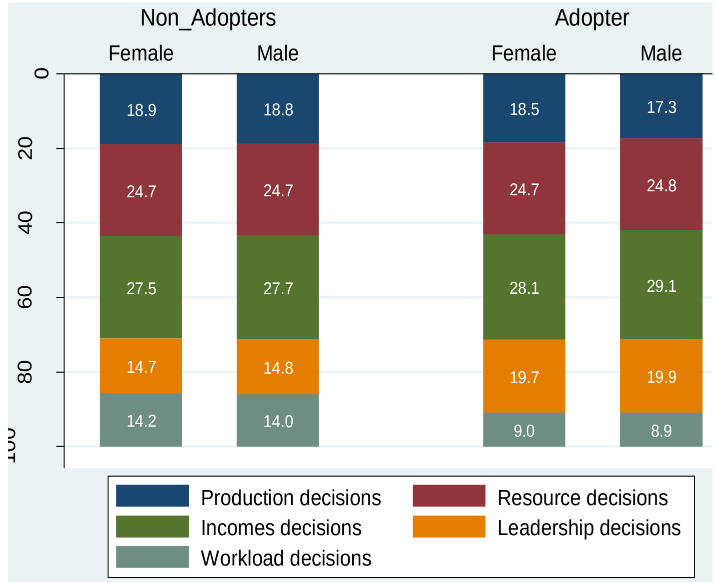

Figure 4: Contribution of each of the five domains to disempowerment by sex and adoption status

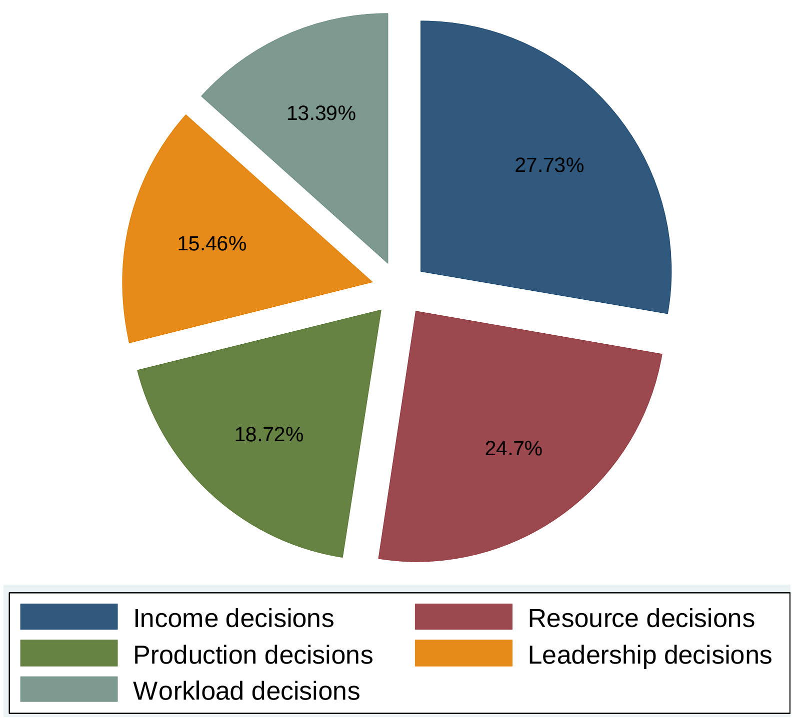

Figure 5: Contribution of each of the five domains to disempowerment

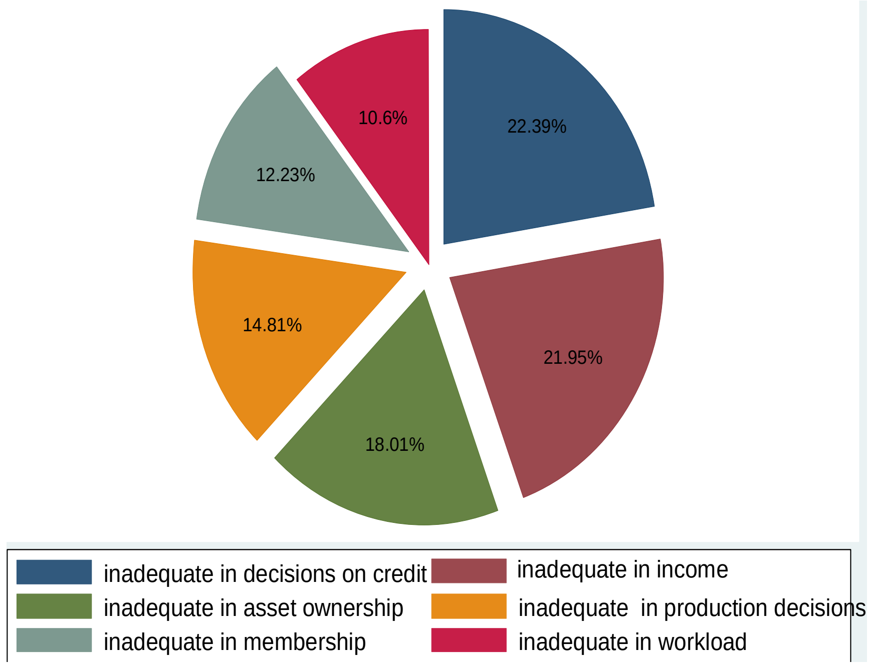

Figure 6: Contribution of each indicator to inadequacy by sex and adoption status

Appendix-B: Supporting Tables

Table B1: The domains, indicators, survey questions, aggregation method, inadequacy cut-offs, and weights in the A-WEAI

Dimension	Indicator name	Survey questions	Aggregation method	Inadequacy cut-off	Weight
Production	Input in productive decisions	Individual has some input, or feels he/she could have, in production decisions	Achievement in two	Individual participates BUT does not have input in decisions; or she does not make the decisions nor feels she could.	1/5
Resource	Ownership of assets	Individual has sole/joint ownership of at least one major asset	Achievement in any if not only one small asset	Household does not own any asset or owns the asset BUT does not own most of it alone	2/15
	Access to and decisions on credit	Individual takes at least one sole/joint decision about use of credit	Achievement in any	Household has no credit OR used credit BUT did not participate in ANY decisions about it	1/15
Income	Control over use of income	Individual has sole/joint input in decisions about income, conditional on participation in activity	Achievement in any if not only minor household expenditures	Individual participates in the activity BUT has no say in decisions about income or does not feels she can take decisions on use of income	1/5
Leadership	Group membership	Individual is a member of at least one group	Achievement in any	individual is not part of at least one group	1/5
Time	Workload	Individual worked < 10.5 hours in the previous 24 hours	NA	Inadequate if works more than 10.5 hours a day	1/5

Source: Adapted from Alkire et al. (2013) and Malapit et al. (2015).

Table B3: Comparison of the WEAI and the A-WEAI: Domains, indicators, and weights

Original WEAI			A-WEAI		
Domains	Indicators	Weight	Domains	Indicators	Weight
Production	Input in productive decisions	1/10	Production	Input in productive decisions	1/5
	Autonomy in production	1/10			
Resources	Ownership of assets	1/15	Resources	Ownership of assets	2/15
	Purchase, sale, or transfer of assets	1/15			
	Access to and decisions on credit	1/15		Access to and decisions on credit	1/15
Income	Control over use of income	1/5	Income	Control over use of income	1/5
Leadership	Group membership	1/10	Leadership	Group membership	1/5
	Speaking in public	1/10			
Time	Workload	1/10	Time	Workload	1/5
	Leisure	1/10			

Source: Alkire et al. 2013 and Malapit et al. (2017).

Table B3: Covariate Balance Indicators before and after Matching: Quality Test.

Outcome Variable	Matching type	Pseudo R^2 Before matching	Pseudo R^2 After matching	LR χ 2 (p − value) Before matching	LR χ 2 (p − value) After matching	Mean standardized bias before matching	Mean standardized bias After matching
5DE[41]	NNM	0.093	0.004	672.66***	15.46	15.1	2.3
	KM	0.093	0.003	672.66***	10.66	15.1	1.8
	RM	0.093	0.004	672.66***	14.56	15.1	2.3
5DE [42]	NNM	0.091	0.005	334.37***	8.87	15.6	2.7
	KM	0.091	0.005	334.37***	9.09	15.6	2.3
	RM	0.091	0.013	334.37***	25.26	15.6	4.5
EG[43]	NNM	0.110	0.004	394.06***	6.62	17.2	2.9
	KM	0.110	0.004	394.06***	6.68	17.2	2.2
	RM	0.110	0.017	394.06***	31.61	17.2	5.6
EG[44]	NNM	0.119	0.005	145.98***	2.99	13.0	3.0
	KM	0.119	0.002	145.98***	0.93	13.0	1.8
	RM	0.119	0.016	145.98***	8.98	13.0	4.9

Note: Statistically significant at the 1 % (***) probability level.

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).

[41] Empowerment in the five domains for the pooled sample.

[42] Empowerment in the five domains for women only.

[43] Empowerment gap for all women.

[44] Empowerment gap for women without parity.

Table B4: A Description of outcome, treatment and explanatory variables

Variables	Description	Full Sample		Adopters		Non-adopters	
		Mean	SD	Mean	SD	Mean	SD
Outcome variables:							
5DE***	Empowerment score in the five domains	0.45	0.23	0.48	0.25	0.45	0.23
EG***	Relative empowerment gap between female and male scores in 5DE	0.55	0.23	0.52	0.26	0.55	0.23
M_o components							
Production***	=1 if inadequate in input in production decisions	0.51		0.47		0.52	
Assets***	=1 if inadequate in asset ownership	0.63		0.60		0.63	
Credit***	=1 if inadequate in access to and decisions on credit	0.78		0.75		0.79	
Income*	=1 if inadequate in control over use of income	0.76		0.75		0.77	
Leadership***	=1 if inadequate in group membership	0.43		0.52		0.41	
Time***	=1 if inadequate in workload	0.37		0.24		0.39	
Treatment							
Adoption Dummy	Household adopted chemical fertilizers jointly with extension services (1 = adopter)	0.14		0.14		0	0
Year	Survey year (three round panel data, 2011, 2013, and 2015)						
Explanatory Variables:							
Religion dummy							
Protestant_dummy***	HHs major religion is Protestant (1=yes)	0.22		0.12		0.24	
Tradition_dummy***	HHs major religion is Traditional (1=yes)	0.01		0.00		0.01	
Pagan_dummy***	HHs major religion is Pagan(1=yes)	0.01		0.02		0.01	
Marital_stat_dummy							
Married_dummy*	Marital status of the individual: is married (1=yes)	0.95		0.96		0.95	
Single_dummy	Marital status of individual: is single (1=yes)	0.01		0.01		0.01	
Separeted_dummy***	Marital status of individual: is separated (1=yes)	0.00		0.01		0.00	
Crop_rotation***	The individual uses the crop rotation method(1=yes)	0.67		0.79		0.65	
House_rooms***	Numbers of rooms in the house (rooms)	1.79	0.96	1.95	0.94	1.77	0.96

Family_size_AE	HH size in adult equivalent (AE)	4.65	1.72	4.70	1.67	4.65	1.73
Mother's Educ	Mother's education status (1 = literate)	0.06		0.05		0.06	
Age	Age of the individual (years)	40.80	13.76	40.73	13.08	40.82	13.87
Age^2	Squared value of age of the individual (years)	1854	1299	1830	1217	1858	1312
Kitchen_type***	Type of kitchen in the house (1=traditional kitchen)	0.34		0.28		0.35	
Light_source***	Source of light in the house (1=electricity)	0.53		0.50		0.54	
Cooking_fuel	Type of cooking fuel (1=electricity or solar energy)	0.01		0.01		0.01	
Water_source***	Type of drinking water source (1=piped or protected water source)	0.57		0.61		0.56	
Toilet_type***	Toilet type in the HHs (1=modern toilet)	0.45		0.51		0.45	

Note: Adopters and non-adopters' characteristics mean differences are significant at the 1 percent (***), 5 percent (**), and 10 percent (*) probability levels respectively.

Source: Author's calculations using WB LSMS data (2011, 2013, and 2015) (2019).