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Doctoral Dissertation

Off-farm Activities, Incomes and Household Welfare in Rural Ethiopia

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To my father Desalegn, my inspiration.

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Preface

The concept of off-farm activities and the link to household welfare has not received the attention it deserves, in particular in policy making circles. Three individual papers study the place off-farm activities have in agricultural commercialization, multidimensional poverty, and consumption smoothing of households in rural Ethiopia. An additional paper examines what drives participation in these activities and the level of income that households generate as a result of such participation.

The papers in this dissertation use a representative, rich, longitudinal dataset with three waves which is a biproduct of a collaborative effort between the Central Statistical Agency of Ethiopia and the Living Standards Measurement Study – Integrated Surveys in Agriculture. The datasets make the empirical backbone of all four papers. Using these datasets, the studies attempt to establish the importance of off-farm activities in a rural Ethiopia.

As one would expect of a Ph.D. dissertation, the contents of this dissertation can be technically involved and suffer from academic jargon specific to the specialization. The chapters in this dissertation are written with academics as the primary readership. However, the implications of the findings in most chapters are accessible to any layman.

This dissertation follows article-based approach. Accordingly, the first chapter provides an introduction into the different topics discussed in each of the articles. The first chapter also maps the interlinking of the remaining article-chapters in the dissertation. Four original papers form the subsequent four standalone and interrelated chapters of the dissertation. Each chapter follows the format of an academic article. Each chapter has an abstract giving a snippet view of the research objectives, methodologies, major findings and implications of the study detailed in the chapter. The introduction section discusses the background for the study. It motivates the research question by clearly indicating where the existing literature on the topic has gaps and the contribution that the author's study makes towards narrowing this gap. The research objectives are, then, outlined. The next section forms a brief overview of the body of literature particular to the research topic. It covers theoretical, methodological and empirical literature. The methodology section outlines the methodological approach in terms of a theoretical framework and an empirical formulation to make the theory econometrically tractable. A results and discussion section presents the key results alongside their meanings in a systematic way. A final section raps up the paper and forwards the implications.

The dissertation is organized as follows. The first chapter gives an introduction to the thesis and a summary of the four papers presented as separate chapters. The second chapter studies determinants of off-farm participation and of income generated from such participation. The third chapter looks at household consumption smoothing behavior and what role off-farm incomes have in this respect. The fourth chapter discusses the effect of participation in off-farm activities on household multidimensional poverty and vulnerability. In the last chapter, the author looks at the link between agriculture and off-farm activities by looking at the effect of off-farm participation and income on agricultural commercialization.

Table of contents

List of Tables

List of Figures

Acronyms

AAU	Addis Ababa University
AEUs	Adult Equivalent Units
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
ATC	Average Treatment Effect on the Control
CIA	Conditional Independence Assumption
CRE	Correlated Random Effects
CSA	Central Statistical Agency
CV	Coefficient of Variation
DAG	Directed Acyclic Graph
DID	Difference-in-differences
EA	Enumeration Area
EEA	Ethiopian Economics Association
ESS	Ethiopian Socioeconomic Survey
ETB	Ethiopian Birr
FDRE	Federal Democratic Republic of Ethiopia
FE	Fixed Effect
FE-2SLS	Fixed Effects Two Stages Least Square
GDP	Gross Domestic Product
GSEM	Generalized Structural Equation Model
GTP	Growth and Transformation Plan
Ha	Hectares
HS	Herfindahl-Simpson
IIASA	International Institute for Applied Systems Analysis
IMR	Inverse Mills Ratio
JEL	Journal of Economic Literature
JIBS	Jönköping International Business School
JU	Jönköping University
LGP	Length of Growth Period
LSMS-ISA	Living Standards Measurement Study – Integrated Surveys on Agriculture
MDG	Millennium Development Goals
MFI	Microfinance Institution
MoA	Ministry of Agriculture
MoFED	Ministry of Finance and Economic Development
MPI	Multidimensional Poverty Index
NBE	National Bank of Ethiopia
NN	Nearest Neighborhood
OLS	Ordinary Least Squares
OPHI	Oxford Poverty and Human development Initiative
PASDEP	Plan for Accelerated and Sustained Development to End Poverty
PCA	Principal Components Analysis
PPS	Probability Proportional to Size
PRSPs	Poverty Reduction Strategy Papers
PSM	Propensity Score Matching
PSNP	Productive Safety Net Program
PSUs	Primary Sampling Units
RE	Random Effect
SD	Standard Deviation

SDG	Sustainable Development Goals
SDPRP	Sustainable Development and Poverty Reduction Programs
SSA	sub-Saharan Africa
TLU	Tropical Livestock Units
UNDP	United Nations Development Program
US	The United States
WB	World Bank
WHO	World Health Organization

Chapter One: Introduction and Summary of the Thesis

Abstract

Ethiopia has been a rural and agrarian society in all known history and remains so to this day. A survey of literature shows that the country's focus has been on agriculture in terms of research interests and development policies. However, these agriculture-based approaches have not delivered on their promises to move rural households out of destitution and poverty. While various alternative growth paths to poverty reduction have been proposed, this thesis focuses on off-farm economic activities. This dissertation makes the case for off-farm activities in four interlinked papers. This chapter gives a summary of the role played by off-farm participation and income on rural households' welfare. It motivates the need for studying the relationship between off-farm income generating activities and rural household welfare in developing countries. It gives a unifying theme and an overarching conceptual framework within which the different studies in the thesis fall. The first of the four papers discusses what drives off-farm participation and incomes. The remaining three papers explore the relationship between off-farm activities and concepts of household welfare – consumption smoothing, multidimensional poverty and vulnerability, and agricultural commercialization. The findings support that off-farm activities are important for rural households' welfare and development policies should take note of this aspect.

Keywords: household welfare; rural economy; off-farm activities; Ethiopia;

JEL classification codes: D10; D60; I00; O10;

1. Introduction and motivation

Archaeological and anthropological evidence has firmly established that Africa is the origin of modern human beings. Lucy from Ethiopia, dating back 3.2 million years, is a prominent case in support of this assertion. Evidence also shows that Africans have contributed to civilization. Some have even dubbed Africa as the cradle of civilization (Fyle, 1999). The Ethiopian alphabet is the oldest on record (Bekerie, 2007). Fast forward, the scene changed dramatically with colonial powers' scramble for Africa in the 1880s. Europe was at a higher level of civilization and managed to use that to its advantage. While the western world continued on the path of economic development and prosperity achieving technological innovations and affluence levels never before fathomable, the supposed cradle of modern human beings and of civilization continues to languish in poverty, famines, diseases and ignorance. This historical context begs the questions, "Where did it go wrong for Africa?" and "How can Africa get back on the road to progress?"

These are profound questions to which no simple answers exist. Post-colonial Africa embraced agriculture as the answer to the second question. Agricultural development was the place to start because the overwhelming majority of the people depended on subsistence farming which was highly inefficient and technologically backward. The post-colonial era was marked by an agricultural boom which translated into export earnings from a few primary agricultural products (Acharya, 1981). However, the path towards economic growth was mired by the vestiges of colonialism and political turmoil. Coup d'états and civil wars remained common even in the 2000s and whatever gains had been made largely dissipated as a result. Some authors also argue that the agricultural policies were bad because they often failed to account for the specific context and the cultural, political, and economic realities of the newly freed nation states.

This was the case in Ethiopia, too. The first attempt to guide economic progress based on what had the semblance of a development strategy was prepared and executed during the Imperial regime. Since 1953, the World Bank and other multilateral organizations have provided support for its economic transformation in the form of structural adjustment programs aimed at improving agricultural production. Agricultural development units were established in various parts of the country as learning centers which helped spawn agricultural inputs considering local contexts (Acharya, 1981; Demeke et al., 2006). However, these attempts were not sustained because the Imperial regime was replaced by the communist Derg regime through a coup. Following 17 years of infighting, civil war, and shifting international alliances, the Derg era came to an end ushering in the transitional government of Ethiopia in 1991 which later formed the Federal Democratic Republic of Ethiopia (FDRE). FDRE promised a more open and inclusive political space and initiated various development strategies. The Poverty Reduction Strategy Papers (PRSPs)[1] formed the core of development planning during this period.

These development strategies coupled with a political resolve on the part of the government saw one of the fastest economic growth rates in the world in Ethiopia in the 2000s. Ethiopia registered double digit growth during this decade (Commission on Growth, 2008). Agricultural production increased beating expectations. Headcount poverty reduced, and the

[1] These are the Sustainable Development and Poverty Reduction Programs (SDPRP) spanning 2002-03 and 2004-05, a Plan for Accelerated and Sustained Development to End Poverty (PASDEP) covering the 2005-06 to 2009-10, and the current development planning instalment, the Growth and Transformation Plan (GTP) with two volumes with the first covering the planning period 2009-10 to 2014-15 and the second expected to cover the period 2014-15 and 2019-20.

nation moved closer to food self-sufficiency. The country also registered remarkable improvements in terms of health, education, and living conditions (Demeke et al., 2006; Mellor & Dorosh, 2010; OPHI, 2018; Shepherd et al., 2018).

Despite these achievements, there were and remain notable concerns about the quality and sustainability of this progress. First, the current growth predominantly comes through heavy government investments. But there is consensus that the government is not as good as the private sector in terms of efficiency, profitability and economic growth (Krueger, 1990). Second, various attempts to move the economic growth base from agriculture to manufacturing have failed. The Ethiopian economy remains predominantly agrarian. In terms of GDP shares, services take up an unusually inflated share[2] of economic activities at 43.6 percent with the industrial sector coming in last with a 21.6 percent share. The manufacturing share of the industrial sector remains very poor. In terms of employment share, agriculture employs 72.7 percent followed by the service sector at 19.9 percent and industry at a meagre 7.4 percent.[3] Third, evidence is building up indicating that agricultural productivity has started stalling. Various studies and reports show that agricultural productivity has started declining as cultivable land continues to run out. By 2001, crop yields had stagnated (Demeke et al., 2006). With an aggressive introduction of productivity improving technologies such as fertilizers, high yield variety seeds, and row seeding practices, cereal productivity saw a substantial increase in the 2000s (Mellor & Dorosh, 2010). However, this too seems to be tapering off as uptake of fertilizers and other yield increasing technologies is showing a less than expected increase (Dercon & Christiaensen, 2011) and agriculture continues to be largely dependent on rainfall.

On top of these indications that the current path of development is unsustainable, further improving the lives of rural households in terms of multidimensional well-being requires marginally higher efforts and greater resources due to what is referred to as the 'last mile problem. Urbanization in Ethiopia is one of the lowest in the world, even by sub-Saharan Africa (SSA) standards. The World Bank's DataBank[4] figures show that the share of urban population in SSA was 40 percent in 2018; however, in Ethiopia it was barely 20 percent. The promise of economic growth that comes with urbanization seems to elude Ethiopia. For example, one study shows that the productivity gains from urbanizing Ethiopia to the level of an advanced country without changing the current level of average productivity could have been as high as six-folds (Mcmillan & Rodrik, 2011).

This thesis argues that off-farm income generating activities come close to the "stone the builders have rejected [that] has become the cornerstone"[5] of the growth and development efforts in Ethiopia. The main economic activity in rural Ethiopia – agriculture – is heavily dependent on rainfall. This coupled with a shrinking farmland and a growing population, makes the lives of rural dwellers more precarious where incomes from off-farm activities come as an invaluable alternative. Households can use the extra income from engaging in off-farm activities to keep their food consumption levels afloat against anticipated and unanticipated shocks. Incomes from off-farm sources can also be used for meeting part of the expenditure requirements for households' health and education needs. Further, evidence shows that off-farm incomes can ease credit constrains faced by rural farm households for

[2] That is considering the stage of economic growth and development that Ethiopia is in.
[3] Source: Index Mundi. Available at: https://www.indexmundi.com/ethiopia/economy_profile.html
[4] Source: World Bank's DataBank analysis and visualization tool. Available at: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=ZG
[5] Psalms 118:22 NIV.

buying agricultural inputs such as fertilizers that boost agricultural production significantly and improve a household's ability to generate saleable agricultural surplus.

These potential benefits of incomes from off-farm sources are at the heart of the structural transformation associated with a nation's economic growth and development. To successfully transition from a predominantly agrarian to an industrial, or even a manufacturing-based economy, better education and improved health is indispensable. In this respect, I argue that off-farm incomes play a pivotal role not only as a lubricant but also as a main source of a household's income stream with meaningful effect on its welfare in rural Ethiopia.

This chapter is organized as follows. The second section discuss the contributions of the thesis and directions for future research. Section 3 reviews important definitional and measurement aspects with respect of off-farm activities and incomes. Section 4 provides a barebones overview of the agricultural household, the theoretical framework which is directly inferred or implied in the papers in this thesis. Section 5 maps the casual path assumed in the papers included in the thesis using a Directed Acyclic Graph (DAG) framework. Section 6 discusses the data used in the thesis. Section 7, the final section, gives a summary of the four papers discussed in this thesis.

2. Contributions of the thesis and directions for future research

This thesis makes some incremental contributions – conceptual, methodological, and empirical. Unlike most discussions on economic development, four inter-related research papers in this thesis position off-farm activities not as a peripheral, shadow, benign, and part of the informal economy, but as an important player that has been neglected in policy attention. The papers in this thesis test the direct relationships between various aspects of rural household welfare. Income from off-farm activities is shown to significantly contribute to the process of smoothing household level idiosyncratic consumption shocks. Participation in these income generating activities also reduces multidimensional poverty of rural households and encourages smallholder agricultural commercialization. The thesis also includes a study of the different factors that determine a household's decision to engage in off-farm income generating activities and drivers of off-farm incomes among households that participate in these off-farm activities.

In terms of conceptual contributions to existing literature, this thesis makes the following contributions. Paper 2 departs from previous research by looking at the consumption smoothing effect of not only aggregate household incomes but also at off-farm incomes in particular. As a departure from previous research, Paper 3 looks at the relationship between off-farm participation and poverty by taking up a nuanced measure of poverty – multidimensional poverty. Moreover, it extends the study of the relationship between off-farm participation and poverty from the present state of household multidimensional poverty to future vulnerability to poverty. In particular, in constructing a vulnerability index, paper 3 builds on previous work to generate a vulnerability index that is comparable to the multidimensional poverty index. Paper 4 moves away from existing literature by arguing that the decision to engage in crop sales is a form of incidental censoring and hence, potential values of income from crop sales for households who have not engaged in off-farm activities could not only be zero but also negative had they engaged.

The research papers that constitute this thesis provide key improvements in terms of causal interpretations of the relationship between off-farm activities – participation, income or both – and the outcome variables studied by better addressing potentially endogeneous selection of households into off-farm income generating activities or participation in agricultural commercialization. In addition, endogeneity rooted in a measurement error of income and simultaneous relationships is also addressed using instrumental variables and panel data techniques. The thesis applies empirical techniques based on parametric and semi-parametric approaches. The Heckman selection model in papers 1 and 4, a contrast estimator and instrumental variables in paper 2 and a difference-in-difference approach in paper 3 are the methods used in this thesis. Moreover, the use of these empirical methods with panel data makes the estimations more robust and less prone to endogeneity problems.

On the empirical front, the research papers in this thesis use panel data from the Ethiopian Socioeconomic Survey (ESS) to confirm and extend the findings of previous research related to households' consumption smoothing behavior, agricultural commercialization, and multidimensional poverty and vulnerability.

Exploiting the richness of the ESS data in terms of the variables and its panel structure, the research papers in this thesis study the heterogeneity of main results by different subsets of the whole study sample. Papers 1 and 2 examine variations of the main results by consumption quintiles. Paper 2 looks at seven different types of off-farm activities. Paper 3 looks at three different categories of off-farm participation and paper 4 discusses households that are either landless or small holders.

Overall, the thesis has the following significant findings. Incentives to engage households in off-farm activities may not translate into increased incomes from engaging in these activities (paper 1). There is a complete smoothing of household consumption at the village level on an annual basis and income from off-farm sources play a significant role (paper 2). Households that engage in family enterprises and those that have members permanently wage employed have lower likelihood of being multidimensional deprived. However, participation off-farm activities does not reduce a household's vulnerability to such deprivations (paper 3). Off-farm incomes and participation encourage decisions to engage in crop sales but do not result in a material subsequent effect on incomes from such crop sales (paper 4).

Even though this thesis has important findings about the role of off-farm participation and incomes in rural Ethiopia, it leaves many questions about the role of off-farm participation and income on economic development unanswered. Paper 2 looks at the role of household consumption smoothing at annual intervals. However, households in developing countries also engage in consumption smoothing intertemporally within a year. But, the nature of the ESS dataset does not allow for this kind of smoothing. Paper 1 looks at income diversification; however, studies in developing countries indicate that diversification, for example as a coping strategy, could occur in the form of asset diversification (Dercon & Krishnan, 2000; Kazianga & Udry, 2006) or a mix of both income and asset diversification (Berloffa & Modena, 2013). Paper 3 looks at the effects of off-farm participation on multidimensional poverty and vulnerability. However, other aspects of household welfare such as food security are also worth looking at. Unlike support for the effect off-farm participation, at least in the high returns'[6] activities category, other studies show that off-farm participation exacerbates food insecurity (Rudolf, 2019). Hence, further research exploring the impact of off-farm participation on aspects of household welfare such as food security needs to be done.

This thesis looks at the household as an economic unit that works together for the common good of all members and does not venture into intra-household dynamics among the members.

[6] Off-farm income generating activities classified under this category are family enterprises and permanent wage employment.

Given the information on the power play between couples in a household in the ESS, a future research direction is restating the research questions in this thesis taking intra-household dynamics into account.

3. Definitions, measurement, and theoretical issues

Literature defines farm income as the value of farm production by a farm family, usually a small holder or the value of the production of primary agricultural commodities (Haggblade et al., 2010). This production is usually for subsistence use of the household and whatever is left is used as seeds for the next season or sold or bartered for other consumption items. Off-farm income, on the other hand, is income generated by a household member working off the farm (Chang & Mishra, 2008). This may include income generated from family enterprise (business) activities, short-term informal rural labor, or formal employment (Bayissa, 2010). Another study defines off-farm or non-farm income as income sourced from any gainful activities off the family farm including farm wage labor, manufacturing, agro-processing, trade, and services (van de Walle & Cratty, 2004). Social safety nets are off-farm in nature as such programs involve earning money or food for a certain amount of work; however, they are often treated as a separate means of household welfare (for example see Bachewe et al. (2016). Another important distinction has to do with income derived from livestock. In studies primarily concerned with cereal production, income from livestock is considered as off-farm income (for example, Nedumaran, 2013). Another source of rural non-farm income is migration earnings (Haggblade et al., 2010). This thesis assumes income from crop and livestock production as farm income while income from all other sources including off-farm wage employment, small non-farm enterprises, safety net programs, remittances, savings, profits and rent as non-farm income.

The terms “off-farm” and “non-farm” can be indistinguishable from each other in terms of activities rural households conduct outside agriculture. However, a more accurate description indicates that there is a clear distinction between the two. The phrase “off-farm activities” is an umbrella term for all activities conducted outside the farm run by the household being considered. Non-farm activities are a subset of off-farm activities. Non-farm activities are all activities a household, via its members, conducts outside of agriculture. These could be wage employment (skilled or unskilled) outside agriculture or self-employment in family run businesses. Off-farm activities are broader in the sense that in addition to non-farm activities, if the household member engages in an agricultural off his or her household’s farm for pay, it will also be considered an off-farm activity (Barrett et al., 2001). For example, if a household member goes off to another family’s farm and gets employed for wage as a daily laborer, then the wage income he or she pockets will be counted as off-farm income to the family in which he or she belongs.

Farm income has traditionally commanded a leading role as a source of households’ welfare and security in rural parts of developing countries. Recently, however, non-farm activities have become an important component of livelihood strategies among rural households. One explanation for this is the diversification drive. According to the portfolio theory, households’ trade-off the relative high mean returns of an activity for reducing risks and maximizing utility (Bezabih et al., 2010). In this respect, employment in non-farm activities is essential for diversification of the sources of a farm household’s means of earning a livelihood.

In the short term, a given household copes with a drought or other causes of harvest shortfalls by, among other things, working in off-farm activities and raising cash to meet welfare down swings. The longer-term welfare effects of non-farm incomes are less obvious. Working off-farm may reduce household food availability and lead to malnutrition because of competition between farm work and food production. However, there is little empirical support for this assumption, (Von Braun & Pandya-Lorch, 2005). On the other hand, off-farm activities have been found to be positively correlated with income and wealth and may offer a pathway out of poverty. Better access to non-farm sources of income are good for household welfare (Holden et al., 2004). Off-farm incomes can also improve farm households' efficiency and performance (Fernandez et al., 2007). Total incomes are significantly higher for rural households that have access to off-farm income (Pfeiffer et al., 2009). Participation in off-farm work significantly increases per head expenditure and reduces household poverty levels (Kousar & Abdulai, 2013). Such long-term effects, however, are not persistent in literature. For example, a recent study found that increasing off-farm work was associated with fewer days worked on staple crops, and in the harvesting and sales stages of the production process (Su et al., 2016). This could result in reduced farm output and wastage during harvest. Moreover, the positive association between off-farm work and wealth and income (in studies such as Bezabih et al., 2010 and Holden et al., 2004) is a double-edged sword since the positive correlation between wealth and non-farm incomes may also suggest that those who begin poor in land and capital face an uphill battle to overcome entry barriers and steep investment requirements for participation in non-farm activities that are capable of lifting them out of poverty (Ellis, 2003).

One of the many ways in which the link between off-farm incomes and rural households' welfare plays out is through the linkage between on-farm production and off-farm participation. The two can be linked directly via production linkages, in which case this linkage is either forward or backward. A forward linkage occurs when growth in the farm sector induces the non-farm sector to increase its activities by investing in productivity or additional capacity for supplying inputs and services to the non-farm sector. A backward linkage is when the non-farm sector is induced to invest in capacity to supply agro-processing and distribution services using farm products as inputs. Indirect expenditure linkages, on the other hand, occur when incomes generated in one of the two sectors are spent on the output of the other. Further, there may be investment linkages between the two sectors, in which case profits generated in one are invested in the other. Such investment linkages are more prevalent where there are constraints on access to credit.

Such linkages between farm production and non-farm incomes eventually raise the issue: "Do off-farm incomes and on-farm incomes compete or complement each other?" There is no clear answer for this. Studies on time allocation decisions by rural household members focus on the benefits accruing to households from diverse sources of both farm and off-farm incomes, mainly through the reduction of income risks (for example, Bezabih et al., 2010). Other studies show that off-farm incomes may ease access to credit (Karttunen, 2009), help smoothen consumption (Berloffa & Modena, 2013; Karttunen, 2009), reduce productive inefficiency (Shittu, 2014), increase agricultural surplus and farm commercialization (Nkegbe et al., 2018).

4. A theoretical framework: the agricultural household model

Agricultural households in developing countries were deemed inefficient and not knowledgeable because of the subsistence agriculture they practice. A seminal work by Boserup (1965) reframed the argument and the operation of agricultural households was considered efficient given the constraints – limited availability of land, environmental calamities, absence of insurance markets, price information asymmetries – in which they operate.

The discussions in all the papers in this thesis are theoretically grounded on the farm household model, which itself is based on the household utility theory. Though the theory of the farm household older roots going back to Chayanov (1966), a comprehensive revisit of the farm household theory and its applications to modeling household behavior were in two important works (Barnum & Squire, 1979; Singh et al., 1985). The model is based on the idea that households in developing countries engage in both consumption and production.

Following is a barebones presentation of the agricultural household model based on Singh et al. (1985). A household is assumed to maximize a utility function given by,

(1.1) $U = U(X_a, X_m, X_l)$

where X_a is consumption from own production, X_m is consumption purchased from the market, and X_l is leisure. Prices for the household's own production, p_a, for consumed goods purchased from the market, p_m, and the opportunity cost of leisure, p_l are given. This utility, $U(*)$, is subject to the household's income constraint,

(1.2) $y = p_a(Q_a - X_a) - p_l(L - F) - q_v V + E = p_m X_m$

where Q_a is the output produced by the household (agricultural or non-agricultural), L is the total labor input into the production process and F is the part that comes from members of the household[7]. The per unit cost of other variable inputs, V, is given as q_v. The households utility maximization is also constrained by the fixed total amount, T, of time available for the household to work on its own farm or off-farm operations or spend on leisure given by,

(1.3) $X_l + F = T$

and the production technology available to the household given by,

(1.4) $Q_a = Q(L, V, A, K)$

where K is capital input and A is land input of the household.

If the production and consumption decisions of the household can be considered separable, then the utility maximizing level of household consumption once the household's production is solved. In developing countries, part of household production is used for own consumption. Households also use own labor as an input in their agricultural production. This amounts to combining consumption and production decisions. Agricultural household models consider the possibility of such interaction between production and consumption decisions. Among fully subsistent households, consumption and production decisions are made simultaneously and are non-separable. However, most agricultural households practice semi-commercial agriculture in which some of the agricultural produce is offered to the market. While the household uses self-sourced inputs, it also purchases some of its farm inputs. In this case, production and consumption decisions may be separately made albeit an indirect relationship. Separability of consumption and production decisions may not, however, hold. A study using data from Turkey showed that the separability assumption does not hold up to empirical scrutiny (Tekgüç, 2012). In another study conducted using the Ethiopian Rural Household Survey data, the author rejects the non-separability assumption (Muller, 2014).

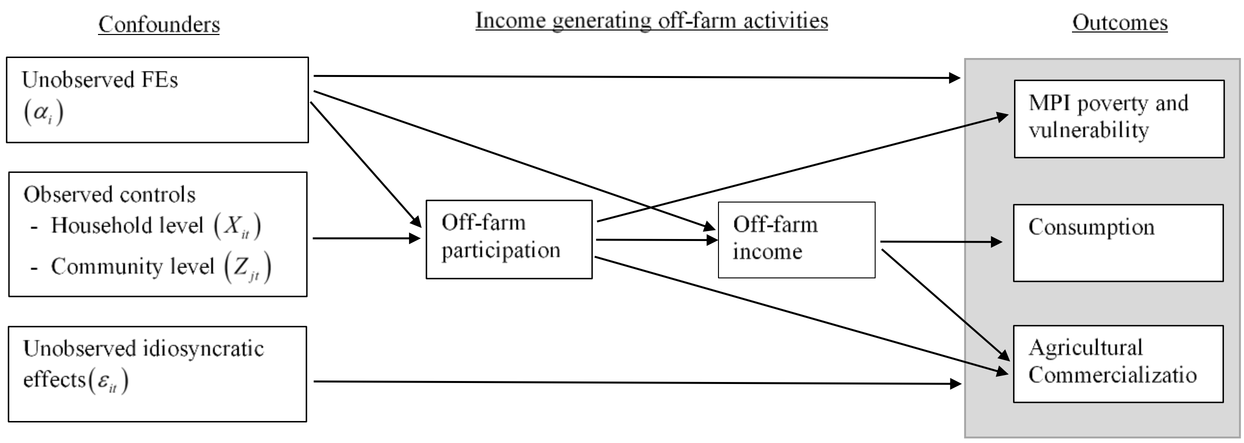
[7] A positive value for $(L - F)$ means labor is hired in by the household; if it is negative the household hires out labor, and if it is zero then all labor input to the production process is by the household members.

Whether the household consumption and production decisions are separable or non-separable, equations (1.1) to (1.4) along with non-negativity constraints, some calculus and algebra, can be used to arrive at reduced form equations mapping the relationships for household, production, consumption, and labor supply.

The research papers in this dissertation approach the household as the smallest unit of economic analysis. In this regard, the papers in this thesis assume that decisions made by household members are made in such a way that the decision each one makes is towards achieving optimum utility for the household first and not the self. In return, utility is distributed among household members on egalitarian basis. These class of household utility models are called unitary household models in the literature (Becker, 1974; Samuelson, 1956). There is strong evidence that household members do not usually root for a common utility optimization of the household (Browning & Chiappori, 1998). Hence, alternative models of household utility have proliferated building their modeling on intra-household bargaining behavior. The problem with these models is that they are highly data demanding requiring detailed information on individual household members. Even though the unitary household model is assumed in the research papers in thesis, household level variables such as total or mean household education, female members, male members are included in the analyses to account for intra-household dynamics following approaches in previous studies (Amare & Shiferaw, 2017).

5. A Directed Acyclic Graph (DAG) approach to causal analysis

This thesis establishes participation in off-farm income generating activities and the income thus earned as important in the quest for the economic transformation of poor, developing countries with Ethiopia as a case in point. The thesis studies four different causal relationships in which off-farm participation in income generating activities and the income thus earned are the key right-hand side variables in the relationship. Following a method of presenting causal relationships in economics literature, the directed acyclic graphs (DAGs) (Pearl, 2009) is to present a unified conceptual framework of the relationship. The concept of DAGs is simple yet very profound in explaining the identification of causal relationships and their clear understanding. Figure 1.1 presents a DAG based conceptual framework of the causal relationships studied in the four papers in this thesis.



Source: Author’s construction.

Figure 1.1. A DAG based causal framework

A causal effect is a contrast between potential outcomes with and without the treatment of interest, other things remaining constant (Rubin, 1974). In a DAG presentation, the vertices (boxes in Figure 1.1) represent random variables which may either be observable or unobservable. The directed arrows represent a causal relationship where the direction of the arrow indicates flow from a cause to an effect variable. When two arrows meet at a vertex, the vertex is called a collider and is said to close 'an open backdoor' and when two arrows radiate away from a vertex, that vertex is a non-collider and is said to open a backdoor to a causal relationship. The key to identifying causal relationships in a DAG framework is to condition it on a vertex if it is a non-collider and not to condition it if it is a collider (Pearl, 2009). Another important DAG concept is an intermediate variable. An intermediate variable is a variable that intermediates the causal path between two variables. A final note before delving into a detailed discussion of Source: Constructed using spatial coordinates for EAs obtained from ESS data

Figure 1.2 is that it is a combination of four DAGs – one for each of the four papers in this thesis.

In paper 1, a Heckman procedure is followed to correct for the selection and a fixed effects procedure (Semykina & Wooldridge, 2010) is used for correction of time invariant individual heterogeneity. In the income equation, the substantive equation, endogenous selection of off-farm participation can be thought of as an intermediate variable. In addition to the non-collider leaks from unobserved household heterogeneity, the leaks due to a selection bias are accounted for by including an inverse mills ratio which exogenizes the effect of participation in the income equation.

In identifying the relationship between households' off-farm incomes and consumption from a smoothing point of view in paper 2, a back door is open due to household level heterogeneity, a non-collider variable problem, which is addressed by applying a fixed effects procedure. Besides addressing the non-collider problem due to household specific heterogeneity, the measurement error of income variables (including off-farm incomes) which is an intermediate variable problem, is addressed using the instrumental variables approach. The village level peer effects of consumption smoothing is identified by using a contrast estimator approach (Suri, 2013).

The effect of a household's participation in off-farm activities on its multidimensional poverty and vulnerability is studied in paper 3. Households were matched on observable characteristics using Kernel weights and propensity scores to address an open back door due to endogenous off-farm participation, an intermediate variable problem. The non-collider variable problem due to unobserved household level heterogeneity is addressed using a difference-in-difference estimator.

In the last paper, paper 4, the effect of off-farm incomes on agricultural commercialization is studied. The study suffers from an intermediate variable problem in the form of endogenous sorting of households into agricultural commercialization. This is corrected using a variant of the Heckman selection model (Bartus & Roodman, 2014). Moreover, the endogeneity of off-farm incomes, another intermediate variable problem, is controlled for by using the lagged values of off-farm participation and incomes.

6. The data

For empirical investigation of the research questions in this thesis, the Ethiopian Socioeconomic Survey (ESS) datasets are used. ESS is regarded as a high-quality[8] multi-topic and multilevel microdata with information on various aspects of households in developing countries. The ESS is part of the Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) project of the World Bank that covers eight countries in Sub Saharan Africa including Ethiopia. The LSMS-ISA is collected with the aim of linking agricultural statistics and welfare. The ESS started out as Ethiopian Rural Socioeconomic Survey (ERSS) in 2011/12 but dropped the "Rural" in the subsequent two waves conducted in 2013/14 and 2015/16 to include large urban areas[9]. However, only the rural sub-sample of the ESS is used in this thesis. This data is representative of rural Ethiopia.

The rural sub-sample of the ESS is a sub sample of the Agricultural Sample Survey (AgSS). The AgSS is bigger but it is not a longitudinal survey. The ESS employed a two-stage probability sampling. In the first stage enumeration areas (EAs) were selected using probability proportional to size (PPS) sampling based on population[10]. In the second stage 12 households were selected randomly within each EA. Ten[11] were chosen to be practicing farming or livestock while the remaining 2 were randomly chosen from those who did not practice agriculture. For the small towns, however all 12 households were selected regardless of whether they practiced agriculture or not. The sub-sample used for this study is representative of rural Ethiopia. Source: Constructed using spatial coordinates for EAs obtained from ESS data

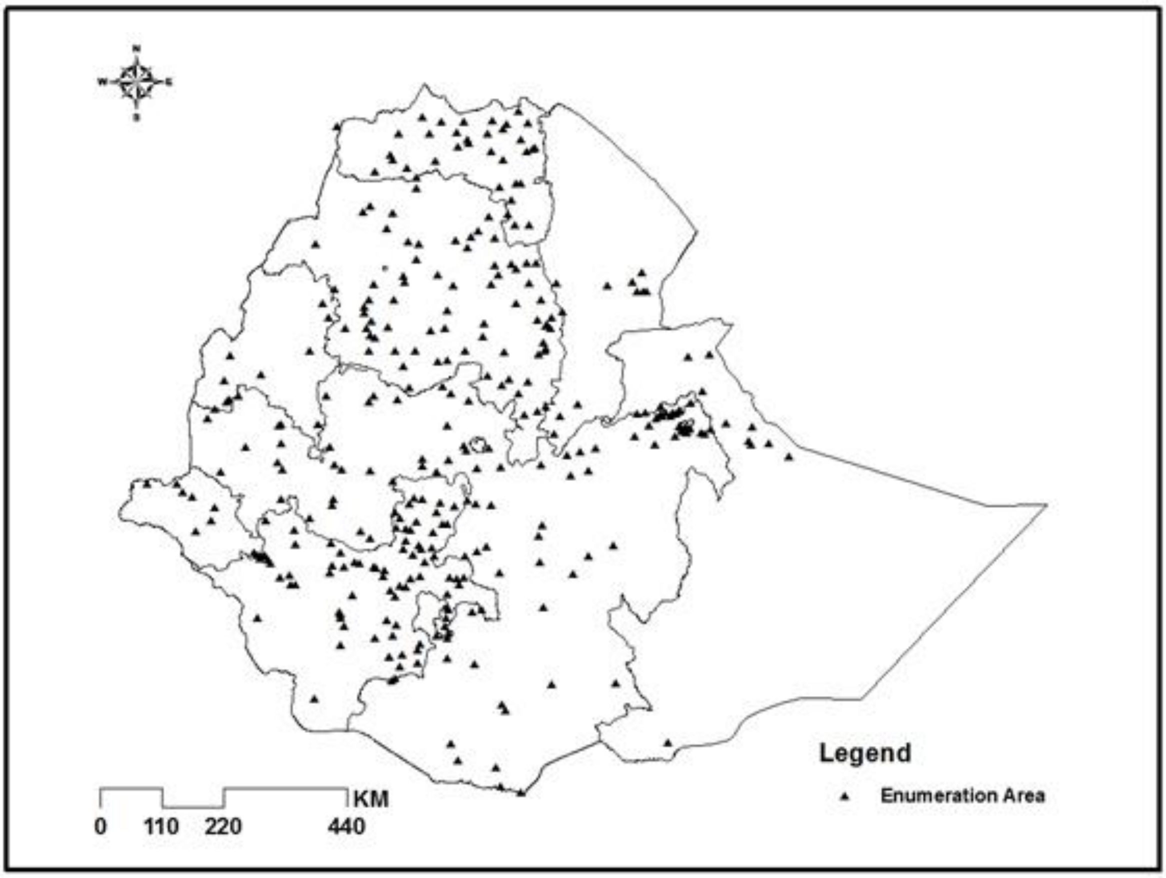
Figure 1.2 gives the distribution of the Primary Sampling Units (PSUs) of the survey.

[8] The quality assurance mechanisms include the use of Computer Assisted Personal Interview (CAPI) platform in the last two waves, use of Global Positioning System (GPS) for

[9] The ERSS also included small towns as urban areas, but these were considered part of rural area. An important distinction between the urban areas included in t the 2013/14 and 2015/16 waves and the earlier urban areas is population size of the settlements. Urban areas with less than 10,000 people were considered small towns and those with more than 10,000 people were considered large towns. This cutoff is set based on the 2007 population and housing census.

[10] The 2007 housing and population census is used for determining the proportions.

[11] This is actually done by selecting 12 households randomly from the 30 households in the AgSS sample.



Source: Constructed using spatial coordinates for EAs obtained from ESS data

Figure 1.2. Distribution of PSUs/ EAs of ESS

A total of 3,969 households were surveyed in 2011/12. This was followed up in 2013/14 with 3,776 households and in 2015/16 with 3669 households. This implied a total attrition of 6.8% for the rural sample of the ESS[12]. In the samples used in four papers included in this thesis, more households were dropped out either because of the target of the study (paper 4) or because of variables with missing information (consumption data for paper 2, and poverty data for paper 3). In each of the papers the author looks if the attrition / non-attrition is explained by the outcome variable(s) in the paper. If that is the case, attrition is controlled for by introducing the inverse of the predicted probabilities of non-attrition as weights in the estimation process. Following the approach used in Van den Broeck & Kilic (2019), the attrition weight is multiplied by the sampling weight provided in the ESS datasets whenever weighing is possible in the estimation process, and this attrition corrected sampling weight is winsorized at 1% of the top end. Another correction procedure followed was to include the predicted probabilities of remaining in all three rounds as an additional explanatory variable in regressions.

[12] Basic information document of the ESS, 2015/16

7. Summary of each paper

The thesis contains four single authored original papers. This section gives a summary of the papers where the motivation, objectives, contributions, methodologies, main findings, and recommendations are listed. All four papers use the Ethiopia Socioeconomic Survey of the LSMS-ISA project of the World Bank.

Paper 1: Household Incomes from Participation in Off-farm Activities in Rural Ethiopia

This paper explores the nature of off-farm diversification among households in rural Ethiopia. It finds answers to two important questions: "What factors determine households' decision to participate in off-farm activities?" and "What variables dictate the level of income that households generate by participating in these activities?"

A farm household model with random effects probit in the first stage and fixed effects in the second stage is used to study this relationship. The results show that households operate at low levels of off-farm diversification and those in the lower consumption quintile experience lower returns to off-farm participation relative to those in the higher quintiles. The econometric results show that being in a rural town has the largest increase on the probability of off-farm participation. Credit access affects participation in but not incomes from off-farm activities. A shock to the household in the form of a food price rise increases off-farm participation but reduces the returns to participation. These results call for innovative insurance products to encourage off-farm participation and for improving off-farm incomes. The results also encourage policy approaches that target expansion of rural off-farm employment opportunities.

Paper 2: Consumption Smoothening and Household Incomes: Do off-farm Incomes Matter?

Rural households in Ethiopia are often characterized as poor smallholder farm families often operating on the edge of subsistence. They are exposed to natural and manmade risks and uncertainties that threaten their existence. This paper examines spatial consumption smoothing and risk sharing patterns by these households using the Ethiopian Socioeconomic Survey (ESS) panel data. It employs a fixed effects two-stage least squares approach for studying consumption smoothing due to household income, and off-farm income in particular. It finds that rural households do fully smoothen their consumption by relying on the incomes of other households in their community. The study also finds that this result is consistent among household consumption quintiles. A key policy relevance of these findings is that short term income shock mitigating policies should not focus on relieving households' idiosyncratic shocks but on correlated shocks that occur at the zonal level or higher administrative aggregations.

Paper 3: Multidimensional poverty, vulnerability dynamics, and the role of off-farm participation in rural Ethiopia

With economic growth and development, the share of agriculture in a country's economy is bound to decline. Hence, growth policies must consider alternative sources of income and employment. This study examines whether off-farm participation has a material impact on rural Ethiopian households' multidimensional poverty and vulnerability to poverty. It uses three waves of panel data from the Ethiopian Socioeconomic Survey spanning five years. It uses a combination of matching and difference-in-difference (DID) technique to study this impact. The results show that participation in small family businesses and permanent wage employment reduce multidimensional poverty but not vulnerability to multidimensional poverty. There are also indications that the impact of participation in off-farm activities varies based on a household's position in the multidimensional poverty spectrum. For example, employment as casual labor or being employed in the Productive Safety Net Program (PSNP) has an impact on a household's odds of being multidimensionally poor for the poorest households. The study recommends that off-farm participation should be encouraged for reducing multidimensional poverty. Vulnerability to multidimensional poverty, however, does not respond to such participation and hence other avenues need to be considered for improving households' future welfare prospects.

Paper 4: Agricultural commercialization and off-farm incomes in rural Ethiopia

This paper explores the role of income generating off-farm activities on agricultural commercialization in rural Ethiopia. Agricultural commercialization is proxied by crop sales. This study measures the effect of a household's decision to participate in off-farm income generating activities and the effect of this income on household crop sales. A Heckman selection model modified to allow for the panel structure of the Ethiopian Socioeconomic Survey data is used to account for the non-randomness of a household's decision to engage in crop sales. The results show that off-farm participation affects the decision to engage in crop sales positively. Off-farm incomes, however, were found to discourage participation in crop sales. Neither, however, had an effect on crop sales. A key takeaway of this result is that though off-farm participation and incomes can improve households' likelihood to commercialize, these do not guarantee an effect on incomes from such commercialization. Additional incentives such as provision of extension services will carry over the likelihood of engagement in crop sales to improvements in incomes from crop sales.

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Chapter Two: Household Incomes from Participation in Off-farm Activities in Rural Ethiopia

(Paper 1)

Abstract

Shrinking plot sizes, a high population growth rate, and environmental degradation call for diversification and alternative income sources in addition to agriculture. This paper explores the nature of off-farm diversification among households in rural Ethiopia. It finds answers to two important questions: "What factors determine households' decisions to participate in off-farm activities?" and "What variables dictate the level of income that households generate by participating in these activities?" The problem of self-selection into off-farm activities is addressed using a variant of Heckman sample selection model. A farm household model with random effects probit in the first stage and fixed effects in the second stage is used to study the relationship. The results show that households operate at low levels of off-farm diversification and those in the lower quintiles experience lower returns to off-farm participation relative to those in the higher consumption quintiles. The econometric results show that being in a rural town has the largest increase in the probability of off-farm participation. Credit access affects participation in but not incomes from off-farm activities. A shock to household in the form of a food price rise increases off-farm participation but reduces the returns to participation. These results call for innovative insurance products to encourage off-farm participation and improve off-farm incomes. The results also encourage policy approaches that target expansion of rural off-farm employment opportunities.

Keywords: off-farm activities; off-farm income; sample selection, Heckman two-stage model

JEL classification codes: D1, J2, J3, O1, Q1

1. Introduction

1.1. Background

Ethiopia remains a rural economy with agriculture contributing the most to the livelihoods of the growing population. More than a quarter of the employment (Geiger & Moller, 2015) and 36 percent of the country's GDP comes from the agriculture sector (UNDP Ethiopia, 2018). Agricultural products including coffee, hides and skins, and pulses are major sources of foreign exchange. Rural households, who are at the heart of the rural economy in Ethiopia, engage in various activities for earning their livelihood including farm production of permanent and non-permanent crops such as cereals, legumes, pulses, coffee, khat, vegetables, fruits, beetroot, and trees. Animal husbandry involving cattle rearing and poultry is an important source of food and income. In addition to these farm-based activities, households also engage in small enterprises usually run by family labor including small breweries, resale of agricultural produce, handicrafts, kiosks, and small cottage industries. These activities usually supplement agricultural incomes and are often run by female members of rural households. Wage employment as a source of income is becoming increasingly important as land fragmentation and rural-urban migration has increased. Wage employment is particularly rewarding for those with higher human capital who are among the relatively better-off. In addition to these sources of livelihood, households also source sizeable incomes from remittances, gifts, rents, and asset sales (Bachewe et. al., 2016).

Off-farm income generating activities are getting increased importance as the rural landscape gets rapidly transformed. For example, off-farm activities are part of the standard development policy prescriptions for improving the welfare of households in drought prone areas (Dorosh & Rashid, 2013) and more so among households headed by women and young adults. However, off-farm incomes in Ethiopia contribute less than 20 percent to household incomes. This is the lowest share among developing countries and lower than the average for Africa (Bachewe et al., 2016). With this low share, off-farm incomes often play a cushioning and complementing role. They mitigate an anticipated or unanticipated drop in household incomes. Studies suggest that farm households in Ethiopia diversify into off-farm employment due to low levels of farm incomes, underemployed family farm labor, or higher marginal returns on their labor (Woldehanna & Oskam, 2001). Moreover, studies in other developing countries show that off-farm incomes may complement farm productivity and production as a source of cash for purchasing farm inputs (Anang, 2017; Bayissa, 2010).

The contemporary context in Ethiopia provides a fertile stage for off-farm incomes to play a key role in current development undertakings. Off-farm income makes up a small share of household income relative to other developing economies. This low base coupled with the rapid economic transformation that Ethiopia is undergoing provides incentives for off-farm incomes to have more and more importance in households' welfare among rural communities. The infancy and current rapid pace of urbanization is another important force that is likely to be a recipe for the important role that off-farm income sources are likely to play in household incomes. Expansion of paved road networks has reduced the economic and psychological costs of migrating in search of off-farm wage employment. These road networks are also driving the development of small-scale family run enterprises. Reduced transportation costs have increased the market reach of these family operated small enterprises. The role of land tenure is another driver of household members' decision to participate in off-farm activities – mainly wage employment and self-employment off the family farm. Though the net effect of off-farm participation is not clear, there is some evidence that insecure land tenure structures could drive up off-farm participation (Deininger et al., 2003). The availability of off-farm jobs may also incentivize participation in these activities. Evidence in literature suggests that availability and access to off-farm employment is limited or not well developed, at best. This curtails diversification even if the drive to diversify is there (Devereux, 2000; Dorosh & Rashid, 2013). The result is unproductive and inefficient labor allocation. This in turn leaves households with reduced livelihood opportunities increasingly exposed to various welfare risks.

In Ethiopia, agriculture remains the dominant source of household consumption and income. Animal husbandry constitutes a considerable portion even though crop cultivation commands a dominant share as a source of agricultural incomes. Off-farm activities are also gaining traction as important sources of household incomes. For example, a study in high potential agricultural areas in Ethiopia shows that 18 percent of household incomes were sourced from off-farm activities and wage income accounted for 55 percent of incomes from off-farm activities (Bachewe et al., 2016). This share is likely to continue as it is the lowest compared to averages for Asia and Latin America. Among the rural economy this transition involves increasing the role of off-farm economic activities.

1.2. Motivation and contribution

Economic growth and development is characterized by a shift away from agriculture to industry and services. Studies show that diversifying into non-farm activities results in higher incomes, better food security, increased farm outputs, and higher resilience to environmental stresses (Gautam & Andersen, 2016). This diversification has picked up pace while the share of agricultural activities has declined in developed countries. Agricultural productivity growth has tapered, land size is continually shrinking, and population growth remains high in developing countries. On the other hand, urbanization is opening new doors and opportunities outside agriculture like casual labor jobs, non-farm work, industry jobs, remittances, and new market opportunities (Hazell & Rahman, 2014). In addition, various social protection schemes such as the Productive Safety Net Program (PSNP) are increasingly accessible to rural dwellers.

These new windows of opportunity not only offer a chance for diversifying but also act as an exit out of agriculture which pays lower returns to labor relative to off-farm activities. This shift is inevitable both from a historical perspective and as a rational decision by households and their members as they seek better productivity of their labor, and the pull and push forces of migration.

Considering these developments, a clearer understanding of the nature of off-farm activities and their effects on household welfare and the channels through which these effects are transmitted is warranted. Off-farm activities may improve household well-being or pose challenges to the poverty reduction agenda. For example, diversification into off-farm activities can be perceived as rewarding in drought prone areas but agriculture maintains an edge in the highlands and other areas with enough rainfall. However, a closer look shows that overcoming infrastructural and marketing hurdles and sustainable environmental management are prerequisites for realizing the payoffs from farm and off-farm engagements (Headey et al., 2014).

This study looks at factors that influence the decisions to participate in off-farm employment and how this translates in off-farm incomes generated by households. Put differently, the objective of this study is identifying the determinants of the decision to participate in off-farm activities and the level of income generated. The specific objectives of this study are:

- Identifying the determinants of the decision to participate in off-farm activities by households, and

- Identifying the determinants of level of off-farm incomes generated by households.

A contribution of this study is that it corrects for households' non-random sorting into off-farm income generating activities in a panel data context. This correction is necessary for improving the properties of the estimates. Given the uniquely rich information on off-farm income sources in the Ethiopian Socioeconomic Survey (ESS), this study accounts for the degree of diversification using seven different sources of off-farm incomes, by far one of the richest categorizations in the literature. Hazell and Rahman (2014) document that, "Income gains at the household level were found to be associated with a shift out of agriculture towards more non-agricultural wage and self-employment income" (p. 390). However, evidence is still inconclusive if this shift is due to farm or off-farm sources. This study establishes whether this increase is of the off-farm income kind. To the author's knowledge no other study uses panel data with a relatively large sample size and representing a huge swath of heterogeneity. These features give this study both empirical richness and methodological superiority.

The rest of this chapter is organized as follows. Section 2 does a review of related theoretical, methodological, and empirical literature. Section 3 discusses the data source and the study variables. It also discusses the theoretical framework, empirical strategy, and identification approaches. Section 4 gives the results of the data analysis with a discussion – both descriptive and inferential – in line with the study's objectives. The final section gives the conclusion and makes some recommendations.

2. Literature review

2.1. Definition and theoretical backdrop

This study modifies the definition of off-farm income generating activities based on Bachewe et al. (2016), and Woldehanna and Oskam (2001) to match with the data used. Off-farm income generating activities are all the activities that a rural farm family or its members engage in that are not on the family's farm. These activities fall in one of seven different sources and three categories (wage employment, self-employment, and residual incomes). Activities that fall in the wage category are permanent wage employment, casual labor, and PSNP employment. Skill based employment, usually paying salaries, are included in this category as well. Wage employment in daily labor activities and PSNP employment do not require any skills. Other family-run enterprises often provide self-employment for surplus family labor during slack agricultural seasons. These enterprises are almost exclusively operated by family members who own them. Another inclusion is migration-based employment away from home. This usually pays back in the form of transfers including remittances to the sending family. The last category is a residual one which includes income from savings, profits, and rents.

Diversification is "the process by which rural families construct a diverse portfolio of activities and social support capabilities in their struggle for survival and in order to improve their standards of living" (Ellis, 1998, p. 4). In the pursuit of welfare, households may engage in livelihood diversification, occupational diversification or just farm diversification (Gautam & Andersen, 2016). This diversification is targeted at reducing anticipated or unanticipated risks and idiosyncratic or correlated risks that rural households face. The presence of these risks implies that diversification is a risk management strategy. A higher level of poverty makes it incumbent upon households to avoid falling below the minimum consumption requirement at all costs including preferring survival over investment options.

Understanding the livelihood strategies of rural households is closely linked to understanding their decisions to participate in farm and off-farm activities and the incomes generated from these activities. The motivation to diversify is discussed in detail by Barrett et al. (2001). In this study, the underlying theoretical explanation for income diversification by farm households is framed in the context of the portfolio theory. In addition to using farm production for household food consumption, rural households sell part of their production and also engage in off-farm activities to provide for non-food items such as clothing, housing, health, and education. Household well-being is often exposed to both foreseeable and unforeseeable decreases due to an event that negatively bears on one or more sources of a household's income. Such examples include crop failure or the sudden death of a household head who is the chief earning member in the household. In anticipation and as a consequence of such negative shocks, rural households do not usually 'put all their eggs in one basket'. In other words, rural households usually go to great lengths to reduce the possibilities of their well-being falling below a subsistence level.

A common scene among rural residents in developing countries is families engaging in multiple income generating activities rather than specializing in one. One activity usually plays a dominant role of income generation while other activities serve as a cushion for warding off the possibility of a fall in the stream of income coming from the dominant source. At first glance, this lack of specialization in one income generating activity suggests that households are operating inefficiently as they will fail to realize economies of scale and of scope.[13] Diversification also kills or slows down the learning-by-doing effect as farm families' engagement is stretched among multiple activities. However, this diversification drive of rural farm families has been recognized as an optimal strategy given the nature of risks and uncertainties that they face (Ellis, 1998). Even though diversification yields smaller expected household incomes, this tradeoff comes with a reduced income variance – a compromise made between high risk-high returns and low risk-low returns scenarios where farm families favor the latter (Ellis, 2000). Households use diversification as a form of insurance against the risks and uncertainties of a fall in their incomes. This risk could be either on the production or consumption side or both.

Households' necessity to stay above the bare minimum requirements of existence motivates diversification, among other factors. A logical follow up question, therefore, is: "What other considerations motivate diversification efforts by households?" Studies show that the level of capital – physical, human, and financial – plays a significant role here. The distance by which households are (or their perceptions) away from the acceptable minimum level of living standards is another driver of participation in off-farm activities, and diversification in general. For example, Ampaw et al. (2017) found that participation in off-farm activities was determined by the level of education of household members and the financial and physical capital at their disposal. Availability of surplus family labor is another factor driving participation in off-farm activities (Woldehanna & Oskam, 2001). On the supply side, participation in off-farm activities is usually determined by the availability of employment opportunities provided by firms in the vicinity, the financial and psychological costs of commuting to and from these firms, the level of wages offered by these firms, and the availability and accessibility to credit to start family run small and micro enterprises. Another important observation in off-farm diversification drives by rural households is the distinction between diversification out of necessity and diversification out of choice (Ellis, 2000). While the latter is voluntary, the former is involuntary. Usually the decision to diversify for poor

[13] There is, however, the possibility of households favoring high return-low risk activities through diversification if the economies of scope is realized (Gautam & Andersen, 2016)

households is out of necessity while it is out of choice for the better-off ones. Necessity entails an act of survival while choice is an investment strategy. A diversification drive is generally considered bad when it is motivated by desperation as those who seek off-farm employment often end up taking jobs with low returns (Woldehanna & Oskam, 2001).

2.2. Methodological literature

The farm household model is the standard starting point for analyzing household welfare and labor markets in rural contexts in developing countries (Singh et al., 1986). Despite its predictive capabilities, the farm household model overlooks the role that social relations play in households' decisions. A natural evolution of the household model is the labor supply and demand model (Janvry & Sadoulet, 2001). In this approach, the decision to participate in off-farm activities is framed as a part of a household's overall welfare decision making.[14]

Studying the implications of participating in off-farm activities on household welfare usually faces the problem of censored data. Observable information is available only for those who are already participants and this decision to participate is a conscious decision and not a random one. Therefore, statistical estimators give erroneous results as underlying assumptions are violated due to the non-randomness of the decision to participate. Previous studies have framed off-farm participation or off-farm income research differently depending on their objectives. A common theme, however, is the attempt to recognize and address the bias that comes from the non-randomness of households' self-sorting decisions to take part in off-farm activities. Boncinelli et al. (2018) used a two-step double hurdle (a negative binomial hurdle) model to study the decisions to participate in off-farm activities. They argued that the decision to participate, the first hurdle, was not random and should be governed by a binomial distribution. Meraner et al. (2015) set up the decision to participate as a binary choice that followed the probit or logistic distribution. Akaakohol and Aye (2014) modeled the impact of diversification on welfare using ordinary least squares (OLS) while the decision to participate in off-farm activities was modeled using the logit binary choice model. Their underlying assumption was that the decision to participate in off-farm activities followed a logistic distribution. Woldehanna and Oskam (2001) modeled the choice to engage in off-farm activities using the multinomial logit approach and modeled the quantity of labor supply as zero-truncated data using a probit model. The Heckman two-step procedure was employed to correct for sample selection in the wage equations. Ampaw et al. (2017) used the propensity score matching (PSM) technique to address households' self-sorting behavior.

2.3. Empirics

Literature on off-farm income generating activities suggests that participation is key in improving household incomes and welfare in rural parts of developing countries. However, there does not appear to be a consensus on the mechanism and contribution of such participation. For example, off-farm wage employment is pursued by households with surplus labor for adding to their incomes. On the other hand, engaging in family enterprises is also pursued as an investment strategy (Woldehanna & Oskam, 2001). Abafita and Kim (2014) identified participation in off-farm activities as one of the key determinants of household food security in Ethiopia. Access to low wage non-farm income can also have a positive

[14] A detailed exposition of this is given in the theoretical framework in the methodology section.

bearing on household incomes; however, such access will also reduce use of farm inputs and agricultural production (Holden et al., 2004).

Where a direct comparison is made to labor's returns from farm and off-farm employment, studies done in developing countries show that there is a positive value of marginal product of labor gap between off-farm self-employment (in family run small enterprises) relative to farm family labor (Woldehanna & Oskam, 2001). However, this positive margin dissipates when controlled for differences in labor use intensity. A recent study using panel data showed that non-farm income reduced agricultural productivity even though it intensified the improved seed use in the smallholder farming context in Uganda (Amare & Shiferaw, 2017). A related study on Nigeria showed that the productivity gap between farm and off-farm labor disappeared once labor use intensity and diversification into non-farm activities were controlled for (Djido & Shiferaw, 2018). Evidence from China shows that there is a strong correlation between farm specialization and increased off-farm labor supply by rural households. In other words, as households migrate away from the farm to engage in off-farm work, members left behind on the farm tend to specialize (Wang et al., 2017). The left behind household members tend to focus on fewer crops and they devote more plots for cultivating a single crop type.

Another feature of the empirical literature on off-farm income generation is the prevalence of heterogeneity in the relationship between welfare and participation in off-farm activities or the income earned from them. As indicated earlier, the nature of off-farm participation is different between the poor and the rich and so are the motivating factors for this participation. Studies suggest that the poor diversify out of necessity and as a form of risk coping strategies while well-off households pursue diversification as an investment strategy where participation is merited by the wage differential as the incentive (Woldehanna & Oskam, 2001).

3. Data and methodology

3.1. Data and variables

This study uses all three waves (2011-12, 2013-14, and 2015-16) of data from the Ethiopian Socioeconomic Survey (ESS), a panel data which is part of the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project. ESS tracked panel households for three waves and collected a multi-topic, nationally representative panel dataset. It contains detailed individual (household members, plot holders, crop, and livestock holders), household, and community level information on rural, small town, and large town dwellings in Ethiopia. The data employed two-stage probability sampling where the first stage involved randomly sampling villages.[15] In the second stage, 12 households were sampled from each enumeration area (EA). The sub-sample used for this study includes 3,239 households from each of three survey waves limited to the rural and small-town sub-sample of the ESS data. The level of non-response and panel attrition rates reported were reasonably low. In the first wave, the non-response rate was 1 percent. The consecutive attritions in waves 2 and 3 were 5 and 1 percent respectively. Overall, the attrition rate was 9.3 percent. The data is hierarchically stratified into five spatial administrative classifications (See Appendix 2.1).

[15] These villages are determined based on CSA's agricultural sample survey's enumeration areas (EA). Though these show the features of villages, they may not satisfy the requirements of a village in the sociological sense (CSA, 2012; CSA, 2017).

Household level data were extracted for the purpose of this study. This is data on household head's characteristics, household characteristics, assets, consumption, income, and community level characteristics. Table 2.1 gives a summary of the definitions and the measurement of the variables in each category. Each category and the variables in each category are identified following standard literature (Bachewe et al., 2016; Barrett et al., 2001; Haggblade et al., 2010; Holden et al., 2004; Reardon et al., 1992; Wang et al., 2017; Woldehanna & Oskam, 2001) and the availability of data covering all three waves of the ESS data.

Sources of households' off-farm incomes were categorized into seven groups: family enterprises, permanent employment, casual labor, Productive Safety Net Program (PSNP), transfers and investments and savings, and rents and profits. Income data from off-farm employment is not considered as part of the household income if the employee is not residing in the household and is remitting his or her income to the household. Income from investments and savings, income from house or land rent, and lottery constitute the final and residual category for this study.

Table 2.1. Definitions and the measurement of variables

Category	Variable	Definition and measurement
Household Head characteristics	Sex	0 = M and 1= F
	Age	In years
	Single headed	Only mother or father present in household = 1
	Occupation	Dominant job of head, 0=agriculture and 1=otherwise
	School years	Highest years of schooling attained
Household wide characteristics	Members	Count for male, female, and total household members
	AEUs	Age-sex adjusted count (Storck et al., 1991)
	Dependents	Count of those members <15 years or >64 years old
	Dependency ratio	% share of members aged <15 and >64 to household size[16]
	Single membered	Households with only one member = 1, otherwise = 0
	School years	Mean, or cumulative highest years of schooling attained for household members as a whole
Household farm characteristics	Temperature	Mean annual levels in degree Celsius
	Precipitation	Total annual in mm
	Elevation	Above sea level in m
	Nutrient availability	Level of nutrient unavailability in increasing order from 1 to 7 where 5 indicates absence of soil and 6 of plot being water devoid
Household asset	Asset Index	First principal component of PCA on 34 asset items
	Housing Index	First principal component of PCA on 12 housing characteristics
	TLU	Livestock in tropical livestock units (Storck et al., 1991)
	land size	Owned, cultivated; in hectares

[16] The dependency ratio is modified to accommodate a case where all household members fall in the dependent category.

Household income[17]	Farm	Income from sale of: (1) permanent and (2) non-permanent crops, income from (3) sale of livestock, and (4) livestock products in ETB
	Enterprise	Income from operating: (1) family run enterprises[18]
	Wage	Wage income from: (2) casual, (3) PSNP, and (4) permanent employment
	Transfers	Transfer from: (5) income from remittances and (6) investments and savings, (7) rents, gifts, and lottery
Shocks		1=shock present, 0=shock absent; The shock is considered if a household identifies it as one of the 3 most severe in the past 12 months among a list of six[19] different shocks.
Community	Nearest distance	From urban center, local market, health post, commercial bank, and MFI; in km
	Agro-ecological zone	Based on WorldClim climate data and 0.0833dd resolution LGP data from IIASA; 8 different zones

The diversification of households into seven different types of off-farm activities studied in this paper is measured using a normalized diversification index – the normalized Herfindahl-Simpson index. The calculation of the index was done following the approach in Djido and Shiferaw (2018). The normalized Herfindahl-Simpson (HS) index not only captures the extent of reliance on a particular income generating activity by a household but also for the number of income sources (dominance) and evenness of activities. HS is calculated as:

$$(2.1)\qquad HS_{it} = 1 - \sum_{k=1}^{n} IS_{kit}^{2}$$

where HS_{it} is the Herfindahl-Simpson diversity index and IS_{kit} is the income share of the k th off-farm activity in total off-farm income. HS_{it} is further normalized to be in the range between zero and one where zero means no diversification and one means full diversification. The diversity index is normalized by applying the formula:

$$(2.2)\qquad NHS_{it} = 1 - \frac{HS_{it} - \left(\frac{1}{n}\right)}{1 - \left(\frac{1}{n}\right)}$$

where n is the number of households for which the diversity index is being calculated.

A summary of household (including head) and community level variables (Appendix 2.2) shows that the average household is about 46 years old and has attended 2.2 years of schooling. A quarter of the households in the study sample were single. Slightly above a

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[17] Income variables were converted to their real annual equivalents using a regional special price index by the Ministry of Finance and Economic Development (MoFED) and supplied with the ESS data. Four types of farm incomes and seven types of off-farm incomes were extracted for this study.
[18] This is also referred to as off-farm self-employment.
[19] These six shocks are death of a household member, illness of a household member, loss of non-farm jobs of household member, drought, flood, food price rises.

quarter of the households were female headed. The average household collectively had total years of schooling just shy of 10 years and a mean of about 2 and a half years. About 4 percent of the households in the sample were single membered. The average household had about 5.56 members which is 4.3 in adult equivalent units. Using a modified dependency ratio, the average household had slightly more than half of its members in the dependents age category.

Though this is not explicitly indicated, a big share of the dependent members' share comes from the young (<15 years). Among households in the study sample, 2 percent had a member who had died, 15 percent had a member who was ill, 18 percent had experienced drought, 6 percent had experienced crop damage, 20 percent reported food price hikes, 11 percent reported input price increases, and 6 percent had a livestock death in the 12 months prior to the survey. The annual mean temperature on a farm family's plot was 19.4 degree Celsius. The total annual precipitation was around 1,080 mm. The average elevation of a plot was 1,849 meters above sea level. The average nutrient availability index of a household's plot fell between a plot with no nutrient constraints and moderate nutrient constraints. The average household was about a kilometer away from the nearest health post, but the closest bank was about 24 km, and the closest MFI was about 14 km. A household member had to travel an average of 16.4 km before reaching a major road, and 40.5 km before finding a population center with 20,000 or more inhabitants living together. A major market was even further where the closest required travelling an average of 66.4 km. Among households in the study sample, about 2 percent lived in the arid agro-ecological zone, which is the harshest of the eight different agro-ecological zones.

Table 2.2 focuses on household assets, incomes, and participation. The average household in the sample owned 2.7 Tropical livestock in TLUs. The same household owned about 1.3 ha of land of which it cultivated 0.93 ha. A farm household generated about Ethiopian Birr (ETB) 610 through sale of farm produce. The total income from off-farm activities was ETB 4,738. This is divided into seven different types of activities. Enterprising activities generated ETB 2,596 followed by wage employment (ETB 1,692), rents, gifts, and lottery (ETB 140), transfers (ETB 137), casual labor (ETB 104), PSNP employment (ETB 54), and savings and investments (ETB 15). Nearly 70 percent of the households participated in cropping and animal husbandry as an income generating activity while 64 percent engaged in at least one off-farm income generating activity.

Table 2.2. Summary statistics of assets, incomes, and off-farm participation variables

Category	Variable	Overall mean	St. Dev.			Overall	
			Overall	Within	Between	Min	Max
Asset	Asset Index	-0.63	2.39	1.74	1.64	-3	39
	Housing Index	-0.52	1.40	0.71	1.21	-3	14
	TLUs	2.71	3.71	1.92	3.17	0	87
	Land owned	1.36	5.62	4.49	3.39	0	427
	Land cultivated	0.93	5.12	4.10	3.07	0	427
Income	Farm	610.32	2,426.95	1,847.88	1,573.50	0	162,499
	Off-farm	4,738.07	43,847.47	34,902.35	26,543.76	0	3,000,362
	Enterprise	2,596.37	18,763.31	13,952.55	12,546.73	0	857,797
	Wage employment	1,691.63	39,598.05	32,107.37	23,178.28	0	3,000,362
	Casual labor	104.14	907.91	732.60	536.33	0	56,961
	PSNP employment	53.80	702.92	565.09	418.10	0	66,266
	Transfers	136.80	802.39	609.44	521.98	0	21,097
	Investments and savings	15.33	289.35	227.04	179.40	0	22,047
	Rent, gifts and profits	139.98	1,143.50	913.45	687.97	0	66,324
Participation	Farm	0.69	-	-	-	0	1
	Off-farm	0.64	-	-	-	0	1
	Family enterprise	0.28	-	-	-	0	1
	Wage employment	0.12	-	-	-	0	1
	Casual labor	0.14	-	-	-	0	1
	PSNP employment	0.11	-	-	-	0	1
	Transfers	0.17	-	-	-	0	1
	Investments and savings	0.02	-	-	-	0	1
	Rent and profits	0.14	-	-	-	0	1
Diversification index (Herfindahl-Simpson)	Off-farm income	0.13	0.19	0.13	0.15	0	0.78
	Total income	0.12	0.18	0.13	0.12	0	0.50

Note: $n_{2011/12} = n_{2013/14} = n_{2015/16} = 3,239$; Source: Author's calculations using ESS data.

3.2. Theoretical framework

The decision to participate in income generating activities, in particular in off-farm activities, can be framed as a labor allocation problem. This can be modeled based on a variant of the agricultural household model. We adopt the approach followed by Owusu et al. (2011) and Anang (2017). Households allocate their time to different activities including off-farm income generating activities. A household maximizes its utility function, given time, budget, production, and non-negativity constraints as:

$$U = U(C, l) \tag{2.3}$$

where C is the household's consumption of goods and l is leisure consumption. The household's time constraint is given as:

$$T = L_1 + L_2 + l \tag{2.4}$$

where T represents the total household time endowment, L_1 is farm work time, L_2 is off-farm work time, and $L = L_1 + L_2$. The household's budget constraint on its cash income, $p_c C$, is given by:

$$p_c C = p_f y + w_1 L_1 + w_2 L_2 + R \tag{2.5}$$

where p_c is the price of goods bought by the household, w_1 is the returns from farm work, w_2 is the returns from off-farm work, y_f is farm output, p_f is the price of the household's farm output, and R is non-labor income. The household faces a production constraint given by:

$$y = f(L_1; A) \tag{2.6}$$

where A is all exogenously given non labor inputs such as land and capital

The Lagrangean of the household utility maximization problem can be given as:

$$\begin{aligned} \Gamma &= U(C, l) + (p_f y_f + w_1 L_1 + w_2 L_2 + R - p_c C) \\ &+ (L_1 + L_2 + l - T) + (y_f - f(L_1; A)) \end{aligned} \tag{2.7}$$

The first order condition for optimal allocation of time between the three activities, farm work, off-farm work, and leisure, is given by:

$$\frac{\partial U}{\partial L_i} = w_i \frac{\partial U}{\partial C} - \frac{\partial U}{\partial L_i} = 0 \tag{2.8}$$

Rearranging (2.8) the returns to farm and off-farm income is given as:

$$w_i = \frac{\partial U}{\partial L_i} \Big/ \frac{\partial U}{\partial C} \tag{2.9}$$

This result shows that the marginal returns to farm and off-farm employment are given as the ratio of the marginal utility from labor to the marginal utility from consumption of goods.

The labor supply functions for farm and off-farm work respectively can be obtained as the reduced form equations obtained by combining the first-order conditions of the maximization problem:

(2.10a) $L_1 = L_1(w_1, w_2, p_y; Z)$ and

(2.10b) $L_2 = L_2(w_1, w_2, p_y; Z)$

where Z is a vector of control variables affecting the household's reservation, w_i^r, and farm and off-farm participation. For a potential market wage w_i^m, the decision of the household to participate in farm, $i = 1$, or off-farm, $i = 2$, labor supply can be given as:

(2.11) $L_i = \begin{cases} 1 & if\ w_i^m > w_i^r \\ 0 & if\ w_i^m \leq w_i^r \end{cases}$

The decision to participate or not is observable, but the reservation wage to participate in off-farm activities is not. A probit or logit model can be used to model this relationship.

The off-farm income, y_{of}, equation for households who participate in off-farm activities is given as:

(2.12) $y_{of} = f(w_2^m, L_2; Z)$

In this study the off-farm equation is setup as a basic earnings function (Mincer, 1974) where income from off-farm activities is measured on the logarithmic scale. Labor augmenting variables such as schooling and experience are included to better capture the quality of off-farm labor. In addition to the schooling and experience of the head, mean and total years of schooling for all household members are also included as explanatory variables to account for intra-household decision dynamics following the argument in Djido and Shiferaw (2018).

3.3. Empirical strategy

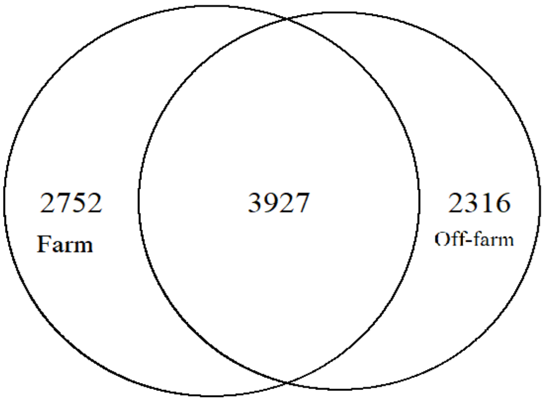
The decision to participate in off-farm income generating activities is based on unobserved characteristics such as a household head's ability to mobilize members and start a small family business or the breadwinner's resolve to keep the household above subsistence consumption. The influence of these unobservable aspects is difficult to measure and results in simultaneity bias.

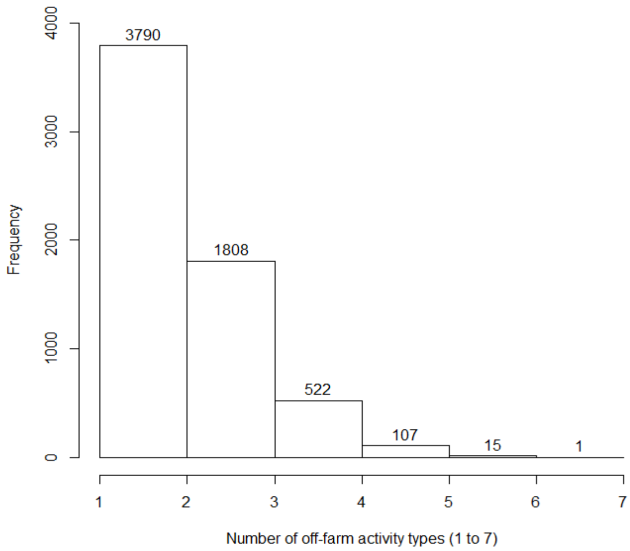
Estimating the off-farm income equation, on the other hand, is prone to selection bias as off-farm earnings are observed only in those households that opted to participate in such activities. There is a suggestion in literature that such opting is usually systematic (Woldehanna & Oskam, 2000; Yúnez-Naude & Taylor, 2001) driven by unobserved characteristics such as households' innate abilities or entrepreneurial tendencies. Such a selection bias results in endogeneity rendering causal inference impossible. This is corrected using a variation of the selection model demonstrated in Semykina and Wooldridge (2010) where a non-selection hazard probability is constructed for each round of the panel data and introduced in the off-farm income equation. To account for the possibility of variations among rounds, the hazard ratio is interacted with the time dummies in the basic equation. A household fixed effects regression was employed to further purge out household specific unobserved variables.

4. Results and discussion

4.1. Descriptive analysis

An analysis of the income transition matrix (Refer to Appendix 2.3) shows that households experienced income gains in most income source categories during the study period. Households participating in farming activities, cropping in particular, gained incomes over the study period. Among off-farm activities households participating in permanent wage employment experienced the largest income gains. Households participating in family enterprises also experienced gains in their incomes. Household participation in income generating off-farm activities shows marked heterogeneity across regional classifications and consumption categories. As indicated in the left panel of Figure 2.1, 43.7 percent (3,927) of the households engaged in both farm and off-farm income generating activities while 30.6 percent (2,752) and 25.7 percent (2,316) engaged in only farm and only off-farm activities respectively. The right panel of Figure 2.1, on the other hand, takes a closer look at the degree of overlap within the seven different types of off-farm activities covered in this study. The bar graph shows the frequency of households engaged in multiple off-farm activities. The graph indicates that 60.7 percent (3,790) engaged in just one type of off-farm activity. Another 29.0 percent (1,808) engaged in two different off-farm activities. The share of households that engaged in three or more types of off-farm income generating activities was barely 10.3 percent (645) of the study sample. These results are indications that even though households are engaged in off-farm income generating activities, these engagements were poorly diversified.





Source: Author's calculations using data from ESS waves I, II, and III.

Figure 2.1. Overlap of participation in farm and off-farm income generating activities

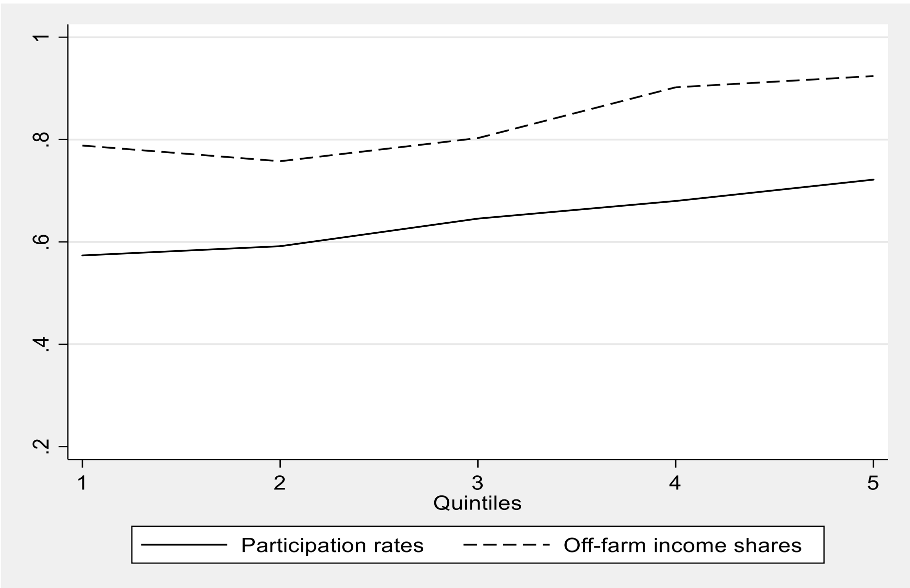
In terms of incomes, households had higher incomes, on average, if they had one more activity in their portfolio of off-farm income activities (see Table 2.3). Households engaging in two off-farm activities had incomes higher by ETB 1,038 than those who engaged in just one off-farm activity. Engaging in three instead of two activities had households generating an additional ETB 1,194. Again, engaging in four instead of three off-farm income generating activities showed a marginal increase of ETB 2,840. But this progression turned negative if there was further diversification. This suggests that more diversification results in higher incomes but only up to a certain extent. Such an interpretation, however, can be misleading as for the 5-activities category, the mean household income is calculated based on 15 households and for the 7-activities category we have only one household.

Table 2.3. Mean household incomes from engaging in multiple off-farm activities

Off-farm Activity count	Frequency	Income	Marginal increment
1	3,790	6,792.8	-
2	1,808	7,830.3	1,037.5
3	522	9,024.4	1,194.1
4	107	11,864.1	2,839.7
5	15	10,091.6	-1,772.4
6	1	6,221.7	-3,870.0
7	0	-	-

Source: Author's calculations using data from ESS 2011/12, 2013/14, and 2015/16 waves.

Another way of looking at the extent of diversification is by disaggregating the study sample by consumption quintiles. Figure 2.2 shows that both the share of income out of total income generated from farm and off-farm income generating activities and participation rates in off-farm income generating activities increases as one moves from the lowest to the highest consumption quintiles. A closer inspection also shows that off-farm participation in the lower consumption quintiles (first and second) is not as rewarding as it is for the higher quintiles.



Source: Plotted using data from ESS 2011/12, 2013/14, and 2015/16 waves.

Figure 2.2. Participation rates and off-farm income shares by consumption quintiles

4.2. Differences between participants and non-participants

There is a marked difference between the participant and non-participant household groups. Table 2.4 reports the mean differences between participants and non-participants in off-farm income generating activities for selected variables[20]. In the household characteristics category of variables, non-participant households had 0.22 more male members, 0.21 more members (in adult equivalent units), and 2.15 percentage points more dependency than participant households. Under farm characteristics, annual precipitation levels were higher by 625 mm for non-participants in off-farm activities. Mean annual temperature level was also higher by about 5 degrees Celsius for the participants. Again, elevation of the household farms above sea level was greater by about 67 meters for non-participants. Among community level variables the distance from the nearest major market was further by about 4.8 km for non-participants. An agro-ecological classification also showed a statistically significant difference between participants and non-participants.

In terms of asset ownership, participant households had better housing conditions and assets as indicated by the statistically significant asset and housing indices. On the other hand, non-participant households had 1.1 more livestock, 0.6 ha more cultivated land, and 0.65 ha more land owned. These results concur with intuition. Lack of land is one triggering mechanism for diversifying into off-farm income generating activities. Moreover, if households have fewer livestock assets, they will participate in off-farm income generating activities. The HS index for farm versus off-farm activities reaffirms this by indicating that households which participated in off-farm activities were more diversified in terms of their sources of income.[21]

[20] Also refer to Appendix 2.4 for a test of mean difference by survey waves for selected variables.
[21] Here income source is considered only in two categories: farm income and off-farm income.

Table 2.4. Differences between non-participants and off-farm activity participants (selected variables)

Category	Variable	Full sample			Quintile					
					1st			5th		
		Diff	S.E.	t-stat	Diff	S.E.	t-stat	Diff	S.E.	t-stat
Household Characteristics	Male members	0.22	0.04	6.12	0.19	2.46	0.08	0.28	3.51	0.08
	AEUs	0.21	0.04	5.11	0.25	2.89	0.09	0.29	3.05	0.10
	Dependency ratio	2.15	0.49	4.37	-1.54	-1.64	0.94	5.89	4.44	1.33
Farm Characteristics	Temperature	-4.90	0.75	-6.51	-3.67	-2.45	1.50	-9.96	-5.23	1.90
	Precipitation	62.50	8.50	7.35	-5.68	-0.34	16.59	37.96	1.90	19.96
	Elevation	67.26	12.51	5.38	59.18	2.35	25.13	149.66	4.77	31.35
	Nutrient availability	-0.03	0.02	-1.66	0.00	0.10	0.02	-0.11	-2.20	0.05
Community level variables (distance to nearest …)	Health center	0.18	0.09	1.90	0.22	1.00	0.22	-0.12	-0.56	0.22
	Commercial bank	1.12	0.60	1.85	1.01	0.82	1.23	-1.33	-0.84	1.58
	Microfinance	-0.07	0.44	-0.17	-0.95	-1.03	0.92	-0.67	-0.56	1.20
	Major road	0.30	0.47	0.64	1.17	1.44	0.81	-2.30	-1.83	1.26
	Population center	-0.40	0.71	-0.57	0.22	0.17	1.33	-2.66	-1.38	1.93
	Major market	4.79	1.07	4.48	6.66	2.47	2.69	-3.68	-1.56	2.36
Agro-ecological zone		0.37	0.04	10.30	0.19	3.07	0.06	0.49	5.19	0.09
Assets	Asset index	-0.56	0.05	-11.16	-0.28	-2.28	0.12	-0.93	-7.21	0.13
	Housing index	-0.57	0.03	-19.73	-0.19	-3.79	0.05	-0.99	-12.13	0.08
	TLUs	1.10	0.08	14.22	0.90	7.14	0.13	1.58	7.48	0.21
	Owned land	0.65	0.12	5.47	0.22	1.14	0.19	0.47	2.96	0.16
	Cultivated land	0.60	0.11	5.56	0.20	1.22	0.17	0.49	4.30	0.11
HS index for farm vs off-farm diversification		-0.17	0.00	-48.22	-0.21	-27.85	0.01	-0.13	-15.53	0.01
Non-participants		3,474			829			540		
Participants		6,243			1,113			1,401		

Note: used a pooled sample Difference = (Non-participant-participant); mean difference by round are given in Appendix 2.4

Source: Author's calculations using all three rounds of ESS data.

4.3. Econometric modeling results

This section discusses two causal relationships. First, it looks at what determines participation in off-farm income generating activities. Second, it studies what drives the extent of income generated from participating in an off-farm activity or a combination of off-farm activities. In finding an answer to the first question, the decision to participate is modeled using a random effects logit regression of the decision to participate on household and community level variables. Table 2.5 reports the results for the statistically significant variables (The full table is given in Appendix 2.5).

Household head's gender had a statistically significant effect on a household's probability to participate in off-farm activities. Female headed households were 7.9 percent, 8.8 percent, and 4.9 percent more likely to participate in off-farm activities relative male headed households. One explanation is that female headed households have lesser entitlements to agricultural inputs such as land and credit relative male headed households. Hence, they engage in off-farm activities that require lesser land and credit. This result is similar to previous studies (Willmore et al., 2012). It is also important to note that female headed households in the lowest consumption quintile had higher probability of engaging in off-farm activities relative to those in the highest quintile.

The maximum years of schooling attained by the household head was found to be statistically significant in determining off-farm participation with positive coefficients both for the full sample and the quintiles. The probability to participate in any one or more of the seven off-farm activities increased by 1.3 percent for every additional year of a head's schooling in the full sample regression; this probability was lower for the richest consumption quintile (1.2 percent) relative to the poorest (1.5 percent). This is an intuitive result and is confirmed by previous studies (Amare & Shiferaw, 2017). More years of schooling gives household heads the advantage of knowledge and skills for starting small businesses or participating in wage employment, other factors remaining the same. It can also be argued that more years of schooling equip household heads to better evaluate signals from the labor market and opportunities for starting a family business so that they can sort household members into different off-farm activities.

Looking at household wide characteristics, the number of females in a household affected the probability of off-farm participation (overall by 1 percent and for the highest quintile by 3.5 percent) positively. Hence, women were more likely to engage in off-farm activities whether they are household heads or members. An increase in the share of dependents in the household by one percentage point increased the probability of participation in off-farm activities by 0.2 percent for the lowest quintile. This means that households in the least well-off quintile are more likely to opt for off-farm activities when they have more dependent members. This result may be indicative of child labor among the least-better-off households. Another explanation could be that these households are more constrained by land and other resources. The closer the household is to the subsistence threshold, the more likely it is to engage in off-farm activities to find a cushion against an unforeseen fall in household consumption. In fact, studies show that in sub-Saharan Africa, the share of on-farm income decreases the higher the welfare quintile becomes (Davis et al., 2017). The results here imply that poor households replace part of this shortfall by engaging in off-farm activities.

Improved housing conditions increased the probability of a household's off-farm participation by 4.0 percent. It can be argued that better housing conditions provide the groundwork for starting a family run business such as a small kiosk or a small restaurant. For example, a kiosk requires a dedicated room and a restaurant may require the family house to have a big enough room where customers can be served food and drinks. Overall, the probability of off-farm participation fell by 1.3 percent for a unit increase in livestock owned. This effect remained negative and significant in both the lowest and highest quintiles. The overall fall in the probability of off-farm participation may be because owning livestock translates into more household income (through sale of livestock or livestock products) and this in turn implies reduced risks of consumption falling below the subsistence threshold. Another explanation could be that households with more livestock units are likely to have more oxen labor to use in on-farm production. However, this explanation needs further exploration using draft oxen ownership. Another interesting finding is that the probability of off-farm participation decreased by 2.0 percent for the lowest quintile and by 1.0 percent for the highest quintile. This seems to suggest that households in the lowest welfare category substituted livestock ownership for off-farm participation more than households in the highest welfare category. As expected, an additional hectare of land reduced the probability of off-farm participation by nearly a percent for the full sample. This probability increased to 1.8 percent for households in the highest consumption quintile. Given the suggestion in literature that off-farm activities usually do not have a differential marginal value product of labor advantage over farm employment (Woldehanna & Oskam, 2001), households with more cultivated land are less likely to participate in off-farm activities. This result is, in fact, insignificant for the lowest consumption quintile but statistically significant and higher for households in the highest consumption quintile relative to the overall sample.

Illness of a household member was found to increase the probability of off-farm participation by 5.4 percent overall. This suggests that households respond to a shock of illness among members by increasing their off-farm labor supply. A similar response is observed when households are exposed to food price rises (4.1 percent). These results show that participation in off-farm income generating activities could be used as a coping strategy against unforeseen illnesses and food price shocks.

Access to credit, as proxied by distance to the closest MFI, was important in the diversification of households into off-farm activities and more so for the least well-off. As expected, Table 2.5 reports that an MFI closer to a household by a kilometer, increased a household's probability of off-farm participation by 0.1 percent for the full sample. This probability increased by an additional 0.1 percent if the household belonged to the lowest consumption quintile. Hence, access to credit is more likely to encourage off-farm participation of the least well-off households in rural communities.

A household' distance from the closest population center had no overall effect on the probability of off-farm participation in both the lowest and highest consumption quintiles. Other studies uncover a negative effect of being close to an urban settlement. Rudolf (2019), for example, found that living closer to urban areas exposed household food security to food price shocks. Another way of looking at this result is in terms of the competing benefits between participation in farm and off-farm activities in response to being closer (and hence lesser transport costs) to markets which appears to cancel out. Belonging to an urban center, however, tells a different story. Usually, residing in a woreda town increased the probability of off-farm participation in the overall (33.9 percent) study sample for households in both the lowest (37.6 percent) and highest (28.8 percent) consumption quintiles. These results indicate that belonging to a small rural town is the single most important driver of off-farm participation decisions in rural Ethiopia. This could be because these townships have much higher demand for wage labor and opportunities for running family businesses. Another reason could be that these settlements provide a much larger market for products of off-farm activities at quite reduced prices due to the higher population density relative to rural settlements.

Table 2.5. Random effects probit regressions for determinants of off-farm participation

	Full sample		Consumption quintiles			
			First		Last	
Variables	Coef.	ME	Coef.	ME	Coef.	ME
Head characteristics						
Sex	0.351***	0.0791***	0.390***	0.088***	0.357**	0.049**
	(0.064)	(0.0143)	(0.123)	(0.032)	(0.164)	(0.025)
Age	-0.003	-0.001	-0.003	-0.001	-0.010	-0.002
	(0.002)	(0.001)	(0.005)	(0.001)	(0.007)	(0.001)
Schooling	0.057***	0.0128***	0.059**	0.015**	0.075**	0.012**
	(0.011)	(0.003)	(0.024)	(0.006)	(0.030)	(0.005)
Household wide characteristics						
Females	0.046**	0.010**	-0.000	0.002	0.236***	0.035***
	(0.022)	(0.005)	(0.040)	(0.011)	(0.069)	(0.010)
Dependency ratio	0.001	0.001	0.007***	0.002***	-0.002	-0.000
	(0.001)	(0.000)	(0.003)	(0.001)	(0.003)	(0.000)
Mean age	0.007**	0.002**	0.010	0.002	0.017**	0.003*
	(0.003)	(0.001)	(0.008)	(0.002)	(0.009)	(0.001)
Assets						
Housing index	1.790***	0.403***	1.835**	0.208**	4.786***	0.451***
	(0.360)	(0.081)	(0.776)	(0.214)	(0.935)	(0.145)
Livestock (TLU)	-0.057***	-0.013***	-0.105***	-0.025***	-0.067***	-0.010***
	(0.006)	(0.001)	(0.019)	(0.005)	(0.018)	(0.003)
Land cultivated	-0.020***	-0.004***	-0.006	-0.001	-0.043*	-0.005
	(0.007)	(0.002)	(0.010)	(0.003)	(0.023)	(0.003)
Shocks						
Illness	0.238***	0.054***	0.212*	0.055*	0.212	0.030
	(0.055)	(0.012)	(0.110)	(0.029)	(0.157)	(0.024)
Drought	0.063	0.014	0.028	0.011	0.053	0.006
	(0.055)	(0.013)	(0.121)	(0.032)	(0.163)	(0.025)
Food price rise	0.180***	0.041***	0.161	0.038	0.219	0.028
	(0.053)	(0.012)	(0.119)	(0.032)	(0.142)	(0.022)
Distance to the nearest …						
Health post	-0.014***	-0.003***	-0.002	-0.000	-0.020	-0.003
	(0.004)	(0.001)	(0.008)	(0.002)	(0.015)	(0.002)
MFI	0.004***	0.001***	0.006**	0.002***	0.003	0.001
	(0.001)	(0.000)	(0.002)	(0.001)	(0.003)	(0.001)
Urban center	-0.000	-0.000	-0.000	-0.000	-0.001*	-0.000*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Rural (Small town=1)	1.506***	0.339***	1.409***	0.376***	1.832***	0.282***
	(0.140)	(0.0303)	(0.277)	(0.070)	(0.395)	(0.056)
Constant	-0.422*		1.114**		1.121**	
	(0.232)		(0.439)		(0.481)	
Observations	8,971		1,765		1,826	
Groups	3,231		1,153		1,201	
ρ	0.461		0.414		0.586	
σ_u	0.925		0.841		1.190	

Wald stat.	634.7	110.6	119.1
LR stat. $(\rho = 0)$	504.1	43.30	63.57

Note: Regressions are controlled for agro-ecological zones, regional fixed effects. and time fixed effects; *** p<0.01, ** p<0.05, and * p<0.1

Source: Author's calculations using data form ESS data.

Factors that determine the amount of income generated from off-farm activities are reported in Table 2.6. This study used a household fixed effects regression adjusted for selection bias using a Heckman (1976) procedure modified for allowing household fixed effects (Semykina & Wooldridge, 2010). Age and schooling of a household head had no statistically significant effect on off-farm incomes. Previous studies have arrived at similar results (Yúnez-Naude & Taylor, 2001). However, schooling had a statistically significant impact (1.5 percent) on off-farm incomes when the total of the maximum years of schooling for all household members was considered. This result suggests that if household members have better education, it can increase their income earnings from off-farm activities. Having a female as the head of a household reduced income generated from off-farm activities by 54.7 percent relative to male headed households for the full sample; this is as expected. However, the opposite was true for households in the lowest consumption quintile as female headed households increased their income earnings from off-farm activities by just above two folds (208.3 percent) relative to male headed households. One plausible explanation for this is that female headed households in the lowest welfare category have better access to financial services specifically tailored for women. One more member, in adult equivalent units, to the household decreased income earned from off-farm activities by 14.8 percent which is confirmed by previous studies (Yúnez-Naude & Taylor, 2001). However, these overall effects were reflected neither among households in the lowest nor in the highest consumption quintiles.

Better housing conditions (36.5 percent for a unit increase in the housing index value) increased income generated from off-farm activities if the household fell in the lowest consumption quintile. Owning an additional livestock, as measured in tropical livestock units, reduced off-farm incomes by 5.1 percent in the overall sample suggesting a substitutability between off-farm activities and livestock. However, the effect of livestock was not reflected either in the lowest or highest quintiles. Owning one more hectare of land increased incomes from off-farm activities by 48.0 percent for the lowest quintile but increase in cultivated land by a hectare reduced off-farm incomes by 57.8 percent for the same category of households. Again, there was no significant effect for the full sample or the well-off quintile.

An increase in food prices was the only shock whose effects were felt in the returns to a household's participation in off-farm activities. In fact, it had a negative effect on the lowest quintile, the highest quintile, and overall. This effect was the largest (70.7 percent) among households in the lowest quintile which is also the most vulnerable to shocks. The reduction in off-farm incomes was 51.4 percent for the highest quintile and 20.2 percent for the full study sample. These results suggest that households are quite vulnerable to food price shocks and that they engage in off-farm activities even if these activities are low paying. As is expected this is more pronounced among households in the lowest consumption quintile.

The distance to the closest commercial bank was found to increase the returns to off-farm participation by 0.5 percent for every kilometer increase. Even though the magnitude of the increase is small, the result goes against intuition. The distance to the closest MFI did not have a statistically significant effect on the returns from off-farm participation.

Among the variables related to farming conditions, a rise in the mean temperature by an additional 0.1 degree Celsius increased the returns to off-farm participation by 22.8 percent for the lowest quintile while it reduced the returns to off-farm participation by 17.7 percent for the highest quintile. There was no statistically discernible effect for the full sample. A meter increase in the elevation of a household's cultivated land translated into a 1.2 percent increase in the returns from off-farm participation for households that fell in the lowest quintile but a 1.0 percent decrease for the highest quintile. The effect on the returns from off-farm participation was 0.2 percent for the full study sample.

Table 2.6. Sample selection corrected household fixed effects regression of ln off-farm income

Category	Variables	Full sample	Consumption quintiles	
			1st	5th
		Coef. (S.E.)	coef. (S.E.)	coef. (S.E.)
Head	Age	-0.005	-0.021*	0.014
		(0.006)	(0.011)	(0.035)
	Schooling	-0.021	-0.025	-0.004
		(0.026)	(0.056)	(0.057)
	Sex	-0.436**	1.126**	-0.363
		(0.208)	(0.482)	(0.666)
Household	Schooling, total	0.015**	0.008	0.029
		(0.007)	(0.020)	(0.019)
	AEUs	-0.138**	-0.111	-0.095
		(0.056)	(0.139)	(0.168)
Household assets	Asset index	0.004	0.011	0.112*
		(0.014)	(0.023)	(0.063)
	Housing index	0.009	0.311**	-0.016
		(0.042)	(0.132)	(0.085)
	TLUs	0.051***	0.114	0.048
		(0.013)	(0.084)	(0.070)
	Land owned	0.016	0.392***	0.021*
		(0.013)	(0.134)	(0.011)
	Land cultivated	-0.032	-0.456***	-0.019
		(0.020)	(0.150)	(0.027)
Shocks	Price rise, food	-0.184**	-0.535**	-0.415**
		(0.083)	(0.234)	(0.204)
Distance to closest …	Commercial bank	0.005***	0.001	0.003
		(0.002)	(0.004)	(0.003)
	MFI	0.000	-0.009	0.006
		(0.002)	(0.006)	(0.005)
Farm variables	Mean temperature	0.030	0.205***	-0.163***
		(0.020)	(0.052)	(0.044)
	Elevation	0.002*	0.012***	-0.010***
		(0.001)	(0.003)	(0.003)
IMR and interactions with round	IMR	-1.157***	-1.183**	0.744
		(0.262)	(0.469)	(0.469)
	2.rnd#c.IMR	0.330***	0.467	-0.008
		(0.117)	(0.317)	(0.439)
	3.rnd#c.IMR	0.499***	0.211	0.160
		(0.136)	(0.318)	(0.522)

Constant	-1.837	-52.862***	57.409***
	(5.868)	(15.232)	(13.457)
Observations	6,202	1,110	1,392
R-squared	0.033	0.188	0.118
σ_u / σ_e / ρ	1.60/ 1.25/ 0.62	2.54/ 1.15/ 0.83	3.86/2.36/ 0.73
F stat. (p-value)	3.58 (0.000)	3.11 (0.000)	2.60 (0.000)

Note: Standard errors are clustered by households; regressions are controlled for agro-ecological zones, regional fixed effects. and time fixed effects; regressions are weighted and corrected for panel attrition.

Source: Author's calculations using data from ESS data

As suspected, sample selection bias was a problem as indicated by the significant coefficients of the non-selection hazard probabilities (IMR) and their interactions with dummies for each of the three rounds in the panel data. However, selection did not appear to be a problem for the household fixed effects regression of the fifth consumption quintile.

5. Conclusion and recommendations

5.1. Conclusion

This study addressed two research questions. First, what factors determine households' decision to participate in off-farm income generating activities, and conditional on a household's decision to participate, what factors determine the level of returns for the decision to participate? The study addressed these two objectives in the context of rural households in Ethiopia using household level data spanning five years and three survey rounds.

The results of the descriptive analysis showed that there was low level of diversification into off-farm income generating activities even though farmers may engage in one or a combination of seven different off-farm activities identified in this study. There was also an overlap between engaging in farm and off-farm activities, a key characteristic of households in developing countries. Participation rates and pecuniary returns increased as one moved up the consumption quintiles. The descriptive analysis also showed that off-farm participation was not as rewarding for households in lower consumption quintiles relative to households in the upper quintiles. This finding was repeatedly confirmed in the econometric analyses.

The results of the econometric analyses strengthened the results of the descriptive analysis and provided evidence of possible causal relationships. In modeling the determinants of income generated from off-farm activities, the problem of non-random sorting of households into off-farm activities was corrected for by using a sample selection procedure for panel data and the basic model was further estimated by way of a household fixed effects regression to purge out endogeneity that may arise from unobserved variables that may be correlated to the explanatory variables and the error term.

The results show that being in a small town was the single most important predictor for increasing the probability of participation in off-farm income generating activities. Having a female as the head of the household was an important driving factor for participating in off-farm activities. Access to credit was also an important driver of participation in off-farm activities and more so for those in the lowest consumption quintile. However, it did not have any significant effect on the returns from off-farm participation. Schooling of the head was a statistically significant determinant for participation but not for the level of returns. Housing conditions generally drove participation in off-farm activities, but this effect was not as pronounced in determining the returns to participation. Illness of a household member and an increase in food prices were key persuasive factors for households to engage in off-farm activities and food prices were also detrimental to the returns from off-farm participation.

From a policy point of view, the econometric results show that there are multiple intervention avenues (variables) available for incentivizing participation in off-farm income generating activities. However, the effects of such incentives may not translate into actual increased income of participation in off-farm activities.

5.2. Recommendations

Based on the results of this study, the following key policy recommendations are forwarded. Given that off-farm employment is an indispensable alternative and a complementary source of income for improving the welfare of rural communities in developing countries, it is imperative to give it due attention. In this respect, a lot needs to be done since the level of diversification of income generation is very low in rural Ethiopia. This low level of diversification of income sources provides significant room for potential improvements in off-farm diversification and household incomes.

Participation in off-farm activities is not as rewarding for households in lower quintiles as it is for those in the upper quintiles. This should be explored further and understood more deeply since off-farm incomes are an important source of household income and welfare.

A policy of expanding townships across the country will have the largest effect on increasing off-farm participation. This will lay the groundwork for diversifying into off-farm activities. However, policies should be cautious to ensure that such participation results in meaningful pecuniary additions to a household's income pot as participation may not necessarily turn into increased earnings.

Diversification can be done not only for income but also for assets. This is not examined in this paper and it might be the case that income diversification and asset diversification may complement or substitute, or households may alternate between the two at a given consumption threshold.

The endogeneity addressed in this paper is the endogeneity of the decision to participate in off-farm activities due to unobserved time invariant variables such as a household's (or household head's) abilities and entrepreneurial tendencies. However, time dependent sources of endogeneity are not formally addressed. For example, if the decision to participate in the next period ($t + 1$) depends on the exposure of a household to shocks in previous periods, then the participation decision will have a time varying element to it that will result in its correlation with the error components. Even though an attempt was made to control for the influence of shocks by including shock variables in the modeling, the list of shocks is not exhaustive and may result in some leftover endogeneity.

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Appendix 2

Appendix 2.1. Distribution of households, EAs, woredas, and zones by administrative region of any given round

Region[22]	Zones	Woredas	Villages	Households
Tigray	5	28	34	340
Amhara	11	64	72	719
Oromia	17	63	65	640
SNNP	21	67	82	799
Other	15	40	77	741
Total	69	262	330	3,239

Source: Author's calculations using data from ESS waves I, II, and III.

Appendix 2.2. Summary statistics of key sample characteristics

Category	Variable	Overall mean	Std. dev.			Overall	
			Overall	Within	Between	Min.	Max.
Household head	Age	46.10	15.42	4.53	14.75	0.00	100
	Age^2	2,363.09	1,575.21	469.72	1,504.07	0.00	10,000
	Schooling	2.12	3.75	1.13	3.58	0.00	18
	Sex	0.26	-	-	-	0.00	1
	Single	0.25	-	-	-	0.00	1
Household wide	Schooling, mean	2.45	2.74	0.90	2.59	0.00	18
	Schooling, total	9.86	10.79	4.30	9.90	0.00	113
	Single membered	0.96				0.00	1
	Male members	2.71	1.68	0.56	1.59	0.00	11
	Female members	2.70	1.50	0.56	1.39	0.00	10
	Size	5.56	2.52	0 .82	2.38	1.00	18
	AEUs	4.30	1.95	0.61	1.86	0.60	14
	Dependency ratio	50.32	23.26	12.53	19.60	0.00	100
Household shock	Death of member	0.02	0.15	0.12	0.09	0.00	1
	Illness of member	0.15	0.36	0.28	0.23	0.00	1
	Drought	0.18	0.39	0.29	0.26	0.00	1
	Crop damage	0.06	0.23	0.18	0.14	0.00	1
	Food price rise	0.20	0.40	0.30	0.26	0.00	1
	Inputs price rise	0.11	0.31	0.24	0.20	0.00	1
	Death of livestock	0.06	0.24	0.19	0.15	0.00	1
Household farm	Temperature	194.06	35.60	3.46	35.43	102.00	294
	Precipitation	1,079.46	402.62	22.03	402.04	144.00	2,031
	Elevation	1,849.75	591.61	55.98	589.01	201.00	3,451
	Nutrient availability	1.42	0.74	0.11	0.73	1.00	7

[22] A note of reminder here, the ESS data is representative of four (Amhara, Oromia, SNNP, and Tigray) of the nine regional states, the biggest administrative classifications. It has a fifth artificial regional classification which lumps all the remaining regions. Though data on each of the remaining regions is not statistically representative, taking them all together as a residual region (CSA, 2017).

Community (Distance from the nearest …)	Health post	1.01	4.44	3.50	2.73	0.00	80
	Bank	24.20	28.54	16.00	23.64	0.00	251
	MFI	14.31	20.81	13.86	15.53	0.00	247
	Major road	16.41	21.98	2.02	21.89	0.00	271
	Population center	40.49	33.66	2.85	33.54	0.00	214
	Major market	66.37	50.55	2.32	50.50	0.30	283
	Agro-ecological zones (arid = 1)	0.02	-	-	-	0.00	1

Note: The survey has missing data for 21, 19, 114, and 471 observations for sex, age, schooling, and occupation variables respectively. n = 3,239, and N = 9,717.

Source: Author’s calculations using data from ESS data.

Appendix 2.3. Income transition matrix

2011 / 12 survey round	Starting income	Obs.	2015/16 survey round crop	Obs.	livestock	Obs.	enterprise	Obs.	wage	Obs.	transfers	Obs.	other	Obs.
crop	538.42	1,580	784.79	1,748										
livestock	744.83	1,597			62.43	1,080								
enterprise	7,545.72	926					11,144.66	902						
wage	9,841.09	414							27,345.54	346				
transfers	788.55	587									750.21	528		
other	764.26	1,215											974.09	1,105

Source: Author's calculations using ESS data.

Appendix 2.4. Difference between participants and non-participants in off-farm activities (selected variables)

Category	Variable	Overall			Round 1			Round 2			Round 3		
		Diff	S.E.	t-stat	Diff	S.E.	t-stat	Diff	S.E.	t-stat	Diff	S.E.	t-stat
Household characteristics	Male members	0.22	0.04	6.12	0.26	0.06	4.44	0.19	0.06	3.21	0.18	0.06	2.81
	AEUs	0.21	0.04	5.11	0.27	0.07	4.00	0.20	0.07	2.82	0.13	0.07	1.82
	Dependency ratio	2.15	0.49	4.37	1.82	0.91	2.00	2.56	0.83	3.10	1.99	0.79	2.52
Farm characteristics	Temperature	-4.90	0.75	-6.51	-2.60	1.32	-1.96	-3.57	1.29	-2.76	-8.51	1.29	-6.59
	Precipitation	62.50	8.50	7.35	71.85	14.90	4.82	43.68	14.59	2.99	72.75	14.72	4.94
	Elevation	67.26	12.51	5.38	24.72	21.98	1.12	45.88	21.52	2.13	131.01	21.51	6.09
	Nutrient availability	-0.03	0.02	-1.66	-0.02	0.03	-0.91	0.01	0.03	0.44	-0.06	0.03	-2.41
Community level variables (distance to nearest …)	Health center	0.18	0.09	1.90	0.50	0.19	2.67	-0.19	0.11	-1.69	0.27	0.18	1.51
	Commercial Bank	1.12	0.60	1.85	4.34	1.17	3.70	-0.45	1.00	-0.45	-0.24	0.95	-0.25
	MF	-0.07	0.44	-0.17	0.75	0.58	1.29	0.10	0.85	0.12	-1.21	0.82	-1.48
	Major road	0.30	0.47	0.64	0.42	0.82	0.51	1.90	0.80	2.39	-1.46	0.81	-1.81
	Population center	-0.40	0.71	-0.57	3.06	1.25	2.45	-1.08	1.22	-0.89	-3.10	1.23	-2.51
	Major market	4.79	1.07	4.48	4.51	1.87	2.41	5.01	1.83	2.73	4.85	1.86	2.61
Agro-ecological zone		0.37	0.04	10.30	0.24	0.06	3.90	0.30	0.06	4.89	0.56	0.06	9.09
Assets	Asset index	-0.56	0.05	-11.16	-0.44	0.13	-3.40	-0.58	0.05	-11.63	-0.58	0.05	-10.95
	Housing index	-0.57	0.03	-19.73	-0.70	0.06	-12.49	-0.51	0.05	-11.05	-0.46	0.04	-10.76
	TLUs	1.10	0.08	14.22	1.18	0.13	9.00	0.99	0.13	7.82	1.14	0.14	7.93
	Owned land	0.65	0.12	5.47	0.60	0.14	4.40	0.60	0.16	3.62	0.75	0.28	2.64
	Cultivated land	0.60	0.11	5.56	0.41	0.11	3.64	0.58	0.12	4.87	0.81	0.28	2.88
HS index for farm vs off-farm diversification		-0.17	0.00	-48.22	-0.18	0.01	-27.69	-0.19	0.01	-31.27	-0.15	0.01	-24.83

Note: Participants: N= 3,474, n1=1,108, n2= 1,213, and n3= 1,153; for non-participants: N=6,243, n1= 2,131, n2= 2,026, and n3= 2,068; Diff = (Non-participant-participant)

Source: Author's calculations using data from ESS waves I, II, and III.

Appendix 2.5. Random effects probit regression of off-farm participation (Full report)

Category	Variable	Full sample		Consumption quintiles			
				1st		5th	
		Coef.	ME	Coef.	Marginal effects	Coef.	ME
Head	Age	-0.006	-0.001	0.002	0.000	0.029	0.006
		(0.009)	(0.002)	(0.018)	(0.005)	(0.020)	(0.004)
	Age square	0.000	0.000	-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Schooling	0.033***	0.008***	0.035	0.010	0.043*	0.009*
		(0.010)	(0.003)	(0.021)	(0.006)	(0.023)	(0.005)
	Sex	0.119*	0.030*	0.093	0.027	-0.040	-0.008
		(0.072)	(0.018)	(0.141)	(0.040)	(0.164)	(0.033)
	Single	0.115	0.029	0.224	0.064	0.280	0.057*
		(0.071)	(0.018)	(0.138)	(0.040)	(0.172)	(0.034)
Household characteristics	Schooling, mean	0.057***	0.015***	0.082	0.023	0.059	0.012
		(0.019)	(0.005)	(0.051)	(0.015)	(0.040)	(0.008)
	Schooling, total	-0.002	-0.001	-0.014	-0.004	0.003	0.001
		(0.004)	(0.001)	(0.009)	(0.003)	(0.011)	(0.002)
	Single membered	-0.337***	-0.086***	-0.210	-0.060	-0.498**	-0.100**
		(0.125)	(0.032)	(0.334)	(0.096)	(0.222)	(0.044)
	Female member	0.043	0.011	0.043	0.012	0.198**	0.040**
		(0.028)	(0.007)	(0.050)	(0.014)	(0.101)	(0.020)
	Dependency ratio	0.001	0.000	0.004**	0.001**	-0.001	-0.000
		(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.000)
Household assets	Asset index	0.023**	0.006**	0.030	0.009	0.026	0.005
		(0.010)	(0.003)	(0.019)	(0.005)	(0.026)	(0.005)
	Housing index	0.127***	0.032***	0.089**	0.025**	0.174***	0.035***
		(0.021)	(0.005)	(0.042)	(0.012)	(0.046)	(0.009)
	TLUs	-0.040***	-0.010***	-0.070***	-0.020***	-0.047***	-0.010***
		(0.007)	(0.002)	(0.018)	(0.005)	(0.014)	(0.003)
	Land owned	0.020	0.005	0.023	0.007	0.066	0.013
		(0.014)	(0.004)	(0.048)	(0.014)	(0.045)	(0.009)
	Land cultivated	-0.035**	-0.009**	-0.023	-0.007	-0.089*	-0.018*
		(0.018)	(0.005)	(0.055)	(0.016)	(0.050)	(0.010)
Shocks	Member illness	0.231***	0.059***	0.184*	0.053*	0.285**	0.058**
		(0.051)	(0.013)	(0.099)	(0.028)	(0.142)	(0.028)
	Drought	0.074	0.019	-0.046	-0.013	0.225*	0.045*
		(0.050)	(0.013)	(0.116)	(0.033)	(0.127)	(0.025)
	Crop damage	0.147*	0.037*	0.243	0.070	0.512**	0.103**
		(0.075)	(0.019)	(0.156)	(0.045)	(0.250)	(0.050)
	Price rise, food	0.201***	0.051***	0.303***	0.087***	0.086	0.017
		(0.048)	(0.012)	(0.110)	(0.031)	(0.116)	(0.023)
Community level variables (Distance to the closest …)	Health center	-0.014***	-0.003***	-0.004	-0.001	-0.009	-0.002
		(0.004)	(0.001)	(0.008)	(0.002)	(0.011)	(0.002)
	MFI	0.003***	0.001***	0.007***	0.002***	0.002	0.000
		(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.000)
	town	-0.001	-0.000	0.001	0.000	-0.004**	-0.001**

		(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.000)
	Major market	-0.002***	-0.001***	-0.001	-0.000	0.000	0.000
		(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Farm characteristics	Mean temperature	0.010***	0.003***	0.003	0.001	0.014**	0.003**
		(0.003)	(0.001)	(0.006)	(0.002)	(0.007)	(0.001)
	Precipitation	-0.000***	-0.000***	0.000	0.000	-0.000*	-0.000*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Elevation	0.000**	0.000***	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Rural	1.042***	0.266***	1.186***	0.341***	0.927***	0.187***
		(0.105)	(0.026)	(0.221)	(0.060)	(0.214)	(0.041)
	lnsig2u	-0.274***		-0.473**		-0.097	
		(0.075)		(0.239)		(0.255)	
	Constant	-2.866***		-1.625		-4.210**	
		(0.965)		(1.940)		(2.146)	
	sigma_u						
	rho						
	Observations	9,643	9,643	1,932	1,932	1,929	1,929
	Clusters	3,239		1,229		1,243	

Chapter Three: Consumption Smoothing and Household Incomes: Do Off-farm Incomes Matter?

(Paper 2)

Abstract

Rural households in Ethiopia are often characterized as poor smallholder farm families who are often living on the edge of subsistence. They are frequently exposed to natural and manmade risks and uncertainties that threaten their existence. This paper examines these households' spatial consumption smoothing and risk sharing patterns using the Ethiopian Socioeconomic Survey (ESS) panel data. It uses a fixed effects two-stage least squares approach for studying consumption smoothing due to household incomes, and off-farm incomes in particular. It finds that rural households fully smoothen their consumption by relying on off-farm incomes of other households in their communities. The study also finds that this result is consistent for all household consumption quintiles. A key policy relevance of these findings is that short term income shock mitigating policies should not focus on relieving households' idiosyncratic shocks and should focus on correlated shocks at the zonal or at higher administrative aggregations.

Keywords: consumption smoothing, off-farm income, household welfare, contrast estimator

JEL classification codes: D10; J20; J22; O12

1. Introduction

1.1. Background

Household consumption in developing countries has peculiar characteristics. In developing countries, households spend a large share of their incomes on consumption with a marginal propensity of consuming as high as 90 percent of their incomes (Berloffa & Modena, 2013). This consumption is mainly composed of food (Suri, 2013). Cereals (mainly maize), wheat, rice, and teff in Ethiopia, have dominated food consumption (Minten et al., 2018). For rural households, consumption peaks during the months following the harvest season and is the lowest at the end of the dry season. These variations in consumption appear to be because of the degree to which rural households are income strapped. Formative studies show that rural households resort to various strategies to cope with these seasonal variations and other unforeseen falls in consumption. These strategies include borrowing from relatives, neighbors, friends, or money lenders; shifting to less expensive food items (cereals such as maize and sorghum); drawing on crop stored for seeding; and selling livestock and assets. Participation in safety net programs or direct government assistance also serve to mitigate consumption shocks (Dorosh & Rashid, 2013; Minten et al., 2018; Pankhurst, 2017). Important non-food expenses include those on education, health and sanitation, housing, and clothes. In addition, owning and maintaining a phone, a radio, a TV set, and entertainment also constitute a form of non-food consumption.

Household consumption, both food and non-food, is mainly financed out of household income. Therefore, exploring household income is key to understanding household consumption smoothing behaviors. A large share of household income comes from agricultural activities. For instance, 65.3 percent of household income originated from agricultural activities while the remaining amount came from non-agricultural household enterprises, wages and salaries, and remittances in 2004/05 (CSA, 2007). Studies also show that there is a clear connection between consumption patterns and income. For example, share of income spent (consumption expenditure) on food falls as one moves up the income ladder. Moreover, consumption of certain food crops such as maize and sorghum are income inelastic while teff and animal products are income elastic (Dorosh & Rashid, 2013; Minten et al., 2018). In Ethiopia, household income comes from different sources. The four main sources are agricultural activities, non-agricultural enterprises, wages and salaries, and remittances. Income sources that fall under agricultural activities are crop production and animal husbandry. Non-agricultural enterprises, on the other hand, refer to such activities as petty trade, wage employment, and salaried jobs. Remittances by migrant household members are also an important component of non-agricultural income. In addition to household income, assistance of different forms also plays a role in household consumption smoothing in Ethiopia. Assistance may come as a social safety net program or in the form of direct aid. The Productive Safety Net Program (PSNP) is a popular social safety net program currently in its fourth phase in the country. There are also food-for-work and cash-for-work programs. Direct food assistance is common during droughts and famines through governmental and non-governmental relief efforts.

Rural households have strong communal mechanisms in place to cushion against idiosyncratic household consumption shocks. The most ubiquitous of this is the institution of *Iddir*. These associations provide insurance against death of a household member, loss of a productive asset such as draft oxen, medical expenses, and food shortage. The habit of establishing pot money for extra expenses on annual celebrations are also commonplace. A very good example of such savings is the *Iqub*. Other informal saving arrangements with smaller pot contributions are run by households' female members (usually mothers). Studies also show that households rely on their neighbors or relatives in times of sudden shocks to their income or consumption (Kinnan & Townsend, 2012; Pankhurst, 2017). The *Iqub* and *Iddir* institutions are roughly limited to farmers' associations or kebeles in terms of spatial coverage. A key feature of these rural associations is that formal insurance mechanisms are absent or limited, and credit markets are dysfunctional (Dercon et al., 2006). Studies also show that households tend to have more children (preferably males) as a long-term risk and uncertainty reduction mechanism to their welfare (Ray, 1998). This paper looks at relying on neighbors and other community members' incomes as an informal means of insurance against household consumption shocks.

1.2. Problem statement

A combination of factors depresses the welfare of rural households in Ethiopia. A typical household in a rural village is a poor smallholder farm family engaged in rain fed agriculture as a means of livelihood. A large share of this household's agricultural produce goes into feeding household members. These household members are underemployed during slack agricultural seasons. Even during the peak season, their productivity does not improve much as agriculture employs technology that is labor intensive and backward (Baye, 2017). Uptake of fertilizers and dissemination of improved seed varieties remains low (Dorosh & Rashid, 2013). Moreover, farmers are exposed to natural and manmade disasters: famines, droughts, wars, ethnic conflicts, and sudden policy changes. These contexts make rural households highly vulnerable to risks and uncertainties. A negative income shock to a household has a detrimental effect on its consumption. Given the state of subsistence, a fall in a household's income could lead to a serious deterioration in its welfare.

Where formal insurance mechanisms are absent or barely functioning, households and communities have long developed informal alternatives for forming a buffer against negative consumption shocks. For example, in the event of the death of a household member in Ethiopia, villagers contribute to a fund set up for the grieving family. In addition, *Iddirs* – informal group insurance schemes – step in as well. Relatives, close friends, and neighbors also provide emotional and financial support (Pankhurst, 2017). Such informal means of insurance have gained the attention of development economists (Kinnan & Townsend, 2012; Suri, 2013; Townsend, 1994).

This paper examines whether households fully pool idiosyncratic consumption risks at the village level and if this is not the case to what extent are the risks partially pooled? It focuses on variations in consumption and the extent to which such shocks are cushioned through community level resources, mainly incomes. Empirical literature is mixed on household consumption smoothing. Some studies have found full risk pooling (Mace, 1991) while others reject the complete smoothing. of household level idiosyncratic consumption shocks (Kazianga & Udry, 2006; Townsend, 1994). Still other studies find only a partial level of smoothing (Suri, 2013).

The test for full consumption smoothing is equivalent to a joint test of two separate hypotheses. One hypothesis is that village level consumption moves one-to-one with household consumption, and that other hypothesis is that all other household covariates do not influence household consumption. Jointly testing these hypotheses has methodological and empirical challenges. On the methodology front, the regression coefficients obtained lack behavioral meaning as community consumption is derived as a community level average of household consumption. To bypass this shortcoming, some studies have taken the leave-out mean where the community level average consumption is computed leaving out the household concerned. Other studies have imposed an additional restrictive assumption of equating the coefficient of community consumption to unity and taking demeaned consumption as the dependent variable instead of household consumption (Townsend, 1994). Where this restriction on regression coefficients can be waived, two sets of separate hypotheses are tested simultaneously to establish the presence of full risk pooling (Mace, 1991). First, the coefficient of community level consumption has to be one, and second the coefficients of all other covariates have to be jointly equal to naught. Where studies have addressed these challenges, their tests have served as a litmus test for the presence or absence of complete risk pooling without yielding information on the extent of partial risk pooling.

One exception in the literature is Suri's (2013) work. She constructs a unified single test of complete consumption smoothing and gives a measure of the extent of partial insurance when the complete insurance hypothesis is rejected. The problem of measurement error, however, has not been adequately addressed in her paper as it does not have provisions for the possibility of measurement errors in household incomes. Measurement errors in household incomes is a common problem in micro-data from developing countries (Deaton, 1992; Townsend, 1994). In addition to the methodological challenges, previous studies have also been limited by data quality and availability.

This paper makes the following key contributions to existing studies. First, unlike previous studies that either focus on negative idiosyncratic household shocks and total household income, this study isolates the extent to which households smooth their consumption using off-farm incomes. Adopting Suri's (2013) contrast estimator, this study explores the role played by off-farm incomes, in addition to aggregate income, on cushioning household level negative idiosyncratic shocks. The study also looks at the heterogeneity of households' consumption smoothing behavior by disaggregating the analysis into consumption quintiles and also examining the risk pooling behavior of broader community structures. It also addresses the endogeneity of household incomes formally using the fixed effects two-stage least squares (FE-2SLS) procedure. This was only partially addressed when Suri (2013) introduced the contrast estimator approach in insurance literature. This study uses the ESS dataset which has one of the largest sample of households and has a nationally representative design. The dataset covers six years and has three panels.

The rest of this paper is organized as follows. Section 2 does a theoretical, methodological, and empirical review of literature on consumption smoothing. Section 3 takes up the methodological framework. In section 4, the dataset used is discussed and the descriptive statistics presented. The econometric results of the data analysis including concerns with specifications, disaggregation, and robustness checks are also discussed in this section. Section 5 gives a conclusion, the key findings, and makes some recommendations.

1.3. Research questions

This research addresses the following research questions:

- What is the extent of consumption smoothing in rural Ethiopia through risk pooling?
- What is the extent of consumption smoothing due to off-farm incomes?

2. Literature review

2.1. Concepts and definitions

Literature defines farm income as the value of farm production by a farm family or the value of the production of primary agricultural commodities (Haggblade et al., 2010). This production is usually by a smallholder farm family and is used as subsistence consumption by the household. What is left over is used as seed for the next season or sold or bartered for other consumption items. Off-farm income, on the other hand, is income generated by a household member working off the farm (Chang & Mishra, 2008). This may include income generated from enterprise activities, short-term informal rural labor, or formal employment (Bayissa, 2010). van de Walle & Cratty (2004) define off-farm income as income sourced from any gainful activity off the family farm including farm labor wage, salaried employment, and income from manufacturing, agro-processing, trade, and services.

Social safety nets are off-farm in nature as such programs involve earning money or food for a certain amount of work off the family farm; however, they are often treated as a separate means of household welfare (for example, see Bachewe et al., 2016). Another important distinction is regarding income derived from livestock. In studies primarily concerned with cereal production, income from livestock is treated as off-farm income (for example, Nedumaran, 2013). Another source of rural off-farm income is migration earnings (Haggblade et al., 2010). This study considers income from crop production and livestock as farm income. Income from off-farm wage employment, salaried jobs, small non-farm enterprise activities, remittances, income from casual labor, and wage employment in PSNP programs is also considered as non-farm income. Direct assistance and income from investment and saving activities, income receipts from profits, rents are also considered a part of off-farm income.

2.2. Consumption smoothing: theories, methodologies, and empirics

Developing economies are characterized by missing markets and where these markets exist, they are usually incomplete and imperfect. This is no different for insurance and credit markets. These circumstances incentivize households to resort to less formal mechanisms of consumption smoothing. These informal insurance mechanisms include exchange of gifts, zero interest loans from extended family or close friends, purchase or sale of assets, grain hoarding, and group based mutual funds such as rotating savings and credit associations (Conning & Udry, 2007).

There is vast literature which documents the theoretical basis for households' consumption smoothing behaviour. A systematic review can be found in Conning & Udry (2007). These theoretical expositions are usually of two kinds. The first kind focuses on a specific insurance mechanism and studies consumption smoothing (Fafchamps et al., 1998; Rosenzweig & Wolpin, 1993). The second focuses on finding out if households smoothen consumption against shocks of various kinds without identifying a particular insurance mechanism (Coate & Ravallion, 1993; Mace, 1991; Seiler, 1998; Suri, 2013; Townsend, 1994). These studies examine whether households, using any and all insurance mechanisms at their disposal, smooth their consumption against idiosyncratic shocks that are specific to them.

This study focuses on the latter approach for studying household consumption behaviour among rural households in Ethiopia. It borrows heavily from Suri (2013).

A benchmark model used for studying consumption smoothing against idiosyncratic household shocks is the full insurance model. This is also referred to as the complete market benchmark model (Townsend, 1994). Other spin-offs include the limited commitment model (Coate & Ravallion, 1993). The full insurance model is a general equilibrium based model. The full insurance model of consumption smoothing posits that if preferences are separable and exhibit weak risk aversion, if all individuals discount the future at the same rate, and if there is no information asymmetry, then optimal risk levels in a stochastic environment imply that all individual consumption will be determined by aggregate consumption. In other words, individual consumption will move together with aggregate consumption. This concept was brought to light by research in financial markets (Wilson, 1968) and later in a study of informal financial markets in developing countries (Townsend, 1994). In a communal context such as a village or other semblance of a community, loss of income, sickness, death of a household member, or any other idiosyncratic shocks should not influence consumption given aggregate consumption at the community level. In this optimal arrangement, it is as if consumption allocations are determined once all crop production of all agents is pooled together and optimally distributed (Townsend, 1994). If a household suffers a sudden slump in consumption, it is either because all other households are experiencing correlated risks or because financial contracting is incomplete between households within communities (Conning & Udry, 2007; Dercon & Krishnan, 2015). This study looks at whether insurance contracting among households in a community is complete and the degree of incompleteness when the complete insurance model is not upheld.

Suri (2013) adopted the peer effects concept from social multiplier literature to household risk pooling behavior. She recast risk pooling behavior as a spillover effect. A peer group effect can be thought of as spillover whereby group outcomes exceed individual outcomes added up to the group level. The extent to which the per person group outcome exceeds the individual outcome is the measure of the peer effect. In the Townsend type modeling of this peer effect, the coefficient of the per person group outcome is a measure of the peer effects. The concept of peer effects is often applied in measuring the effects of social experiments on student performance controlling for or measuring the effects of the peers.

For the purpose of illustrating how peer effects work and associated measurement challenges, an analogy is drawn for measuring the effect of reducing class size on student performance in a student peer group context. A student's performance may increase due to a reduction in the class size to which she belongs. In measuring the effect of this reduced class size on test scores, one has to control for the student's characteristics and classroom variables.

There is, however, another force at work that is not captured in this measurement – the influence of the student's peers. It is believed that if the student belongs to a peer group which is better performing, then her performance will improve compared to the test scores she would have had had she belonged to a peer group with students who performed poorer than she did. This influence of peers on the student is a kind of spillover that meddles with the measurement of the effect of class size on her performance. Therefore, in addition to student and classroom variables, the peer effect phenomenon has to be accounted for in measuring the effect of class size on student performance. Using the same logic, Suri measures a household's consumption smoothing behavior in the context of the community to which it belongs. If a household's consumption falls relative to the community average, this will be corrected (completely or partially) by other, relatively well of members of the community and hence the household's consumption will be smoothed. Any risk to a household's consumption is pooled at the community level where spillovers help as a cushion. Suri takes up Boozer and Cacciola's (2001) contrast estimator to identify this peer effect on household consumption. This contrast estimator is a comparison of how an average household in a given community responds to an income shock with respect to its consumption decisions, relative to how the community responds on average. The contrast estimator is superior to previously used tests for cross-sectional consumption smoothing because it provides an omnibus test for Pareto allocation of household risks in a community and the extent of this efficiency.

The introduction of peer effects in studying consumption smoothing creates methodological and empirical challenges. Chief among the conceptual challenges is that the individuals who make up each peer group may not be exogenously formed and so may bias the outcome of the social experiment. Another concern is what is referred to as the reflection problem (Manski, 1993). Even when the peer groups are formed exogenously, individual and group outcomes may be formed simultaneously. This makes it difficult to establish a causal effect because individual outcomes could just be a reflection of group outcomes.

On the empirical front, survey data on household incomes is susceptible to measurement errors. This leads the estimation of peer effects of income on consumption to endogeneity problems. Previous studies have addressed these methodological and empirical problems. Some studies have omitted households with severe income measurement problems (Townsend, 1994). Suri (2013) addressed the reflection problem but not the problem of the measurement error in the income variable. This study addresses endogeneity through the use of valid instruments.

Even though mixed, the empirical results of household consumption smoothing cluster in favor of rejecting the theoretical position of complete consumption smoothing. A review of the household consumption smoothing literature indicates that a few studies fail to reject the full insurance hypothesis of household consumption based on data for the US (Cochrane, 1991; Mace, 1991) and sub-Saharan Africa (Suri, 2013). Later studies have rejected the full insurance hypothesis (Dercon & Krishnan, 2015; Kazianga & Udry, 2006). A more recent study posed asset smoothing as a competing household objective for consumption smoothing (Berloffa & Modena, 2013). This is based on an income threshold where a household shifts from consumption smoothing to asset smoothing. Their study found that non-poor households smooth their consumption out of incomes while poor households relied on their labor supply to smooth their consumption and did not draw on their incomes. Singh and Kumar (2012) found partial consumption smoothing among households within the same village or within their own ethnic group.

This paper explores community consumption spillover effects on households. The approach also identifies the role played by off-farm income in household consumption smoothing.

3. Methodology

3.1. Theoretical framework

A test for the complete risk sharing hypothesis can be developed by supposing that households organize themselves into risk sharing groups – villages. An average household maximizes a common preference instantaneous utility function. Within each group, consumption is efficiently allocated in each period over the lifetime of any given household. Consider an economy with a single village, no credit markets, for T periods with S possible states of nature each with a probability of realization, π_s . Let's suppose that these probabilities do not vary by household and over time. Income is exogenously given for each i household in each state of nature s at time t as y_{ist} . These assumptions are relaxed in the empirical analysis. Then the utility of a household in this hypothetical single village economy can be given as:

$$(3.1) \quad U_i = \sum_t^T \beta^t \sum_s^S \pi_s u_i(C_{ist})$$

where β is the discount factor and C_{ist} is state-time contingent consumption of household i, and $u_i(.)$ is each possible state-time contingent realization of utility for household i. The $u_i(.)$s are assumed to behave well. Equation (3.1) gives a state-time weighted utility of household i. The optimization problem for the single village economy can be given as:

$$\begin{aligned} & Max \quad \sum_i^N \omega_i U_i \\ (3.2) \quad & s.t. \quad \sum_i^N C_{ist} = \sum_i^N y_{ist} \quad \forall s,t \\ & and\ C_{ist} > 0 \quad \forall s,t \end{aligned}$$

where ω_i gives the household specific weights of their utility functions which are used for arriving at the village economy's aggregate utility, and N is the number of households in the community. If we restrict the households in the economy to just two as i and j, the first order conditions will yield:

$$(3.3) \quad \frac{u'(C_{ist})}{u'(C_{jst})} = \frac{\omega_j}{\omega_i} \quad \forall i, j, s, t$$

Imposing an exponential utility function[23] for tractability as $u_i(C_{ist}) = -\frac{1}{\sigma} e^{-\sigma C_{ist}} \quad \forall i, s, t$, the first order condition can be re-written as:

$$(3.4) \quad \frac{e^{-\sigma C_{ist}}}{e^{-\sigma C_{jst}}} = \frac{\omega_j}{\omega_i} \quad \forall i, j, s, t$$

Taking the natural logarithms of Equation (3.4) will get:

$$(3.5) \quad C_{ist} = C_{jst} + \frac{1}{\sigma}\left(\ln \omega_i - \ln \omega_j\right)$$

This result holds for both households i and j in the utility maximizing village economy. The result obtained in Equation (3.5) can be extended to a village of N households where each household is optimizing in relation to the rest of the households in the village economy. This can be stated as:

$$(3.6) \quad C_{ist} = \overline{C}_{st} + \frac{1}{\sigma}\left(\ln \omega_i - \ln \overline{\omega}\right)$$

[23] This impact of applying different functional forms of the utility function on the results of the test for Pareto allocation of risks is discussed in Mace (1991). Recent studies use log transformed variables instead of levels as in Equation (3.5) (Berloffa & Modena, 2013). This study also follows a log transformation.

where $\overline{C}_{st} = \frac{1}{N}\sum_{i=1}^{N} C_{ist}$ and $\overline{\omega} = \frac{1}{N}\sum_{i=1}^{N} \omega_i$ are village average values. The second expression on the right-hand side of Equation (3.6) can be interpreted as the household fixed effect. This fundamental result of Equation (3.6) is that household consumption co-moves one-to-one with community level aggregate consumption irrespective of the history of households' preferences, demographic characteristics, or exposure to idiosyncratic shocks when the village economy operates at optimal utility. The implications of this are that any sudden fall in the consumption levels of a given household is smoothed out fully unless that sudden fall is common to all other members causing aggregate village consumption to fall. Hence, shocks to household consumption in a village are fully insured by other members provided that households in the community maximize their respective utilities.

Equation (3.6) can be tested by running an ordinary least squares regression of household consumption on aggregate village consumption and household specific characteristics for each household for a given village as:

$$(3.7) \quad C_{it} = \beta_i \overline{C}_t + \delta_i X_{it} + \alpha_i + \varepsilon_{it}$$

where X_{it} is a matrix made up of vectors of household characteristics including income, assets, preferences, demographic characteristics, and idiosyncratic household shocks; ε_{it} is the error term; and α_i is the household fixed effect which is also the regression constant. Here, the test for full insurance translates into a joint test: $\beta_i = 1$ and $\delta_i = 0$. But this requires a long panel data and applying this approach for economy wide tests of the full insurance hypothesis where there are multiple village units runs into an econometric problem (this is discussed in Townsend, 1994) rendering a behavioral interpretation impossible. To work around this, one can restrict the coefficient on the community aggregate consumption variable to unity and use the deviation of household consumption from the village aggregate as the dependent variable. In this workaround, a $\beta_i = 1$ restriction is imposed and the test boils down to just $\delta_i = 0$. This means, if $\delta_i = 0$ holds then households are completely insured against idiosyncratic consumption falls by the community to which they belong and hence there is full consumption smoothing. But the data demanding nature of the test remains and averaging consumption over villages still makes the coefficient on the aggregate consumption variable, $\overline{C}_t$, lack a behavioral meaning.

3.1.1. The contrast estimator

This study follows literature on peer effects and constructs a contrast estimator for risk sharing (Boozer & Cacciola, 2001; Suri, 2013). In this approach, risk sharing is considered a spillover effect which emanates because a household belongs to a village. The intuition behind the contrast estimator is that when a household experiences a fall in its consumption relative to the village average, that fall in consumption will be mitigated by other peer households in its community that were not as unfortunate. This mitigating effect can be conceived as a positive spillover effect of the higher aggregate consumption in the village. Conceptualizing household consumption smoothing as a village spillover effect is superior to the Townsend (1994) type tests because it provides a test not only for absence of full insurance but also provides measures for the level of partial smoothing in the absence of full insurance. In addition, it also combines two separate tests for the full insurance hypothesis into one (Suri, 2013). The contrast estimator is a comparison of how a household in a given village responds to a fall in its consumption relative to how the village responds to fall in consumption on average. To model this comparison, consider the following version of Equation (3.7):

$$(3.8) \quad C_{ij} = \beta \overline{C}_j + \delta X_{ij} + \gamma Z_j + \alpha_i + \varepsilon_{ij}$$

where C_{ij} is consumption of household i in village j, $\overline{C}_j$ is village level average consumption, X_{ij} refers to household specific covariates such as demographics, incomes, assets, and negative shocks, Z_j refers to village level covariates, and α_i refers to household fixed effects. Following Suri (2013), the household fixed effects, α_i, is omitted for ease of showing how the contrast estimator works; however, it is accounted for in the empirical work.[24]

Using Equation (3.8) we can measure the response of a household's consumption to changes in income using a village fixed effects regression. The household fixed effects regression removes village level covariates including correlated shocks and peer effects. Based on Equation (3.8), the household fixed effects are:

$$(3.9) \quad C_{ij} - \overline{C}_j = \phi^W \left(y_{ij} - \overline{y}_j \right) + \delta^W \left(X_{ij} - \overline{X}_j \right) + \left(\varepsilon_{ij} - \overline{\varepsilon}_j \right)$$

where variables with a bar are village averaged values; ϕ^W is the within village estimator of change in household consumption in response to a unit change in average village level income; and δ^W is a vector of coefficients of other household characteristics such as income, assets and demographic characteristics. The village level average consumption response can be recovered by running a between effects regression. The between-villages effects regression specification of Equation (3.8) can be given as:

$$(3.10) \quad \overline{C}_j = \phi^B \overline{y}_j + \delta^B \overline{X}_j + \gamma^B Z_j + \overline{\alpha}_j + \nu_j$$

Among the coefficients of this between effects regression, ϕ^B measures the time averaged response of household consumption to time averaged village level consumption. The between effects coefficient contains the spillover effects while the within effects coefficient gives individual variations purged of the village level peer effect.

Using the coefficients obtained from the two regressions, a contrast estimator can be constructed for measuring the spillover at the village level. This gives village level peer effects – the additional consumption smoothing that comes as a result of a household being a part of the village.

Having obtained ϕ^W and ϕ^B from Equations (3.9) and (3.10) respectively, the contrast estimator can be constructed as (Boozer & Cacciola, 2001; Suri, 2013):

[24] A household fixed effects model was used in the empirical analysis. As there is no mobility of households between villages by construction, the village level fixed effects become redundant. This result also corresponds with the fundamental result of complete smoothening as stated in Equation (3.6).

(3.11) $\hat{\beta} = 1 - \frac{\phi^W}{\phi^B}$ [25]

This $\hat{\beta}$ is an estimate of the β in Equation (3.7). At least three interesting scenarios can be drawn from the possible values of $\hat{\beta}$. If $\phi^W < \phi^B$, then there is a positive consumption spillover due to income and $0 < \hat{\beta} < 1$. The value of $\hat{\beta}$ gives the extent of partial risk pooling. A limiting case is when $\phi^W = 0$, then $\hat{\beta} = 1$[26] and there is a one-to-one co-movement of household level consumption and village level aggregate consumption due to incomes and hence complete risk pooling. When $\phi^W = 0$, it means that a change in household income does not affect household level consumption. Therefore, the contrast estimator combines the two testable requirements of full insurance into one estimate. If $\phi^W > \phi^B$, then there is a negative consumption spillover at the village level and $\hat{\beta} < 0$. Another important result is when $\phi^W = \phi^B$. In this case there is no spillover and $\hat{\beta} = 0$. If $\hat{\beta} \neq 1$, then the null hypothesis of full insurance is rejected and the value of $\hat{\beta}$ gives us the extent of partial insurance. A $\hat{\beta}$ value other than unity may not, however, mean partial insurance. It may mean that either the risk pooling group used is not the right aggregation, or that households are not pooling risks over space but across time.

3.2. Empirical strategy

The contrast estimator addresses the peer effects phenomenon; however, the measurement error problem still persists. This study applies the fixed effects two-stage least squares (FE-2SLS) (Semykina & Wooldridge, 2010) regression to tackle the problem of measurement error in income. In the first stage, income is instrumented by household wide characteristics namely aggregate years of schooling for the household, aggregate highest years of schooling for the household, number of dependents, male members, aggregate age of household members, and household size. In addition, to account for zero income entries for households, particularly off-farm incomes, a dummy variable was introduced in the instrumenting equation. The justification behind using these household wide characteristics is that they are related to a household's ability to generate income and not so much to household consumption (see Table A3.1 in Appendix). In the second stage, household consumption is regressed on the instrumented income variable and other covariates.

An important feature that this study picked on is that the test for consumption smoothing can be constructed using the coefficients of the income variable (Deaton, 1992; Townsend, 1994) and not the household shock variable as done by Suri (2013). Suri also alludes to the possibility of this approach. To pin down the role played by off-farm incomes on household consumption smoothing, the income variable was split into its farm and off-farm components and contrast estimators were calculated using the respective coefficients. In addition to examining contrast estimates for village level risk pooling, the study also looks at villages risk pooling behavior at the woreda level by collapsing the data into village aggregates.

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[25] Suri (2013) adopts Boozer and Cacciola's (2001) measure of the contrast estimator to Townsend's (1994) full insurance hypothesis.

[26] For this result to hold, the denominator, ϕ^B, must be positive.

The level of randomness in the selection of individual households into villages and woredas is another important identification concern. If households are not assigned randomly into these groups, then differences in consumption smoothing are not due to risk pooling but rather due to unobserved community specific characteristics. The ESS survey design addresses this partly as villages are randomly selected and so are households in each village.

Another problem is the appropriateness of the risk pooling group that is assumed. For example, it might be that households pool risks at the woreda level and we miss this pattern by assuming risk pooling at the village level. It could also be that villages pool risks at the woreda level. The evidence available, however, suggests that in the absence of formal insurance mechanisms, households enter into informal reciprocity arrangements in smaller groups where the possibilities of moral hazards and information asymmetry are greatly reduced and contract enforcement mechanisms are stronger (Conning & Udry, 2007). For example, in Ethiopia informal insurance mechanisms such as *Iddir* and *Iqub* do not usually network past the kebele administrative area (Dercon et al., 2006). For this study, enumeration areas (EAs) were taken to be the village equivalent units for idiosyncratic household risk pooling. EAs, with a few exceptions, are composed of 150 to 200 households who live together and are delineated by recognizable landmarks. These EAs are delineated within kebeles, the smallest administrative classification in Ethiopia (CSA, 2012).

3.3. Data and variables

This study uses the Ethiopian Socioeconomic Survey (ESS) panel dataset - multi-topic household level data on agricultural statistics and other household income activities. Important precautions were taken to ensure the quality of the data.[27] The ESS has an added quality of inter-country comparability as Ethiopia is one of eight countries where the LSMS-ISA project is being implemented. Currently ESS is panel data with three waves, each two years apart.[28] Though the last two ESS rounds have data on both urban and rural areas of Ethiopia, this study focuses only on rural dwellings which constitute 80 percent of the country's population (Hill & Tsehaye, 2015). Data used in this study spans seven regional states (excluding Addis Ababa and other major towns)[29] and is representative of rural Ethiopia. Table 3.1 gives a summary of the distribution of administrative classifications included in the study sub-sample.

[27] A detailed description of the survey design, data collection entries, and information on quality controls can be found in the basic information documents of each survey. These documents are made available with the ESS data.

[28] Round 1 was carried out in 2011-12, round 2 in 2013-14, and round 3 in 2015-16.

[29] Definitions from the basic information document for any of the three rounds. These documents are made available with the ESS data.

Table 3.1. Distribution of administrative classifications in the study sample

Regional state	Number distribution			
	Zones	Woreda	Villages (EAs)	Households
Tigray	5	28	34	1,020
Amhara	11	64	72	2,157
Oromia	15	62	66	1,953
SNNP	17	66	82	2,397
Other[30]	21	40	77	2,223
TOTAL	69	260	331	9,750

Source: Author's calculations using data from ESS waves I, II, and III.

Even though the sub-sample is restricted to rural Ethiopia, it includes not only rural communities but also small rural towns (CSA, 2017). The survey used a two-stage probability sampling. The EAs were the primary sampling units (PSUs) which were selected using probability proportional to size (PPS) sampling. Within each EA, 12 households were selected. However, due to dropouts and lack of important information, the average number of households in each EA is less than 12. After cleaning and balancing the three panels of the survey and excluding households from major urban areas in the second and the third rounds, the final sample size was 3,250 households in each round. These households were distributed among 331 EAs. The 331 EAs in turn were distributed among 260 woredas and finally, the 260 woredas were distributed into 69 zones (refer to Table 3.1).

Following literature on consumption smoothing, four categories of variables were extracted for the study sub-sample: demographic and education variables, consumption variables, income variables, and asset variables. Table 3.2 gives a summary of the definitions, measurements, and characteristics of each of these variables. Consumption, income, and asset variables were adjusted for age-sex distribution by taking adult equivalent units (AEUs) as the deflator.

Table 3.2. Definitions and measurements of the study variables

Category	Variable (household level	Definition and measurement
Demographics and education	Sex of head	Male=0, Female=1
	Households with a single member	No=0, Yes=1
	Members adhering to >1 religion	No=0, Yes=1
	Highest level of education (of head, of any member)	No education=0, basic primary=1, general primary=2, general secondary=3, preparatory=4, undergraduate=5, postgraduate=6
	Age (of head, members' average, members' cumulative)	Years
	School years (head's, members' cumulative)	Years
	Dependency ratio	Percent
	Household size (total, male, female, dependents)	Count

[30] This residual category includes smaller regional classifications – Benishangul, Gambella, Somali, and Afar regional states.

	Adult equivalent units (AEUs)	measured as per Storck et al. (1991)
Consumption	Village consumption	value of annual household consumption expenditure at 2013 prices averaged for a village, excluding[31] the household being considered
	Total consumption	value of annual household food consumption and non-food consumption expenditure at 2013 prices
	Food consumption	value of annual food consumption at 2013 prices
Income	Total income	value of annual income aggregating crop, livestock, and off-farm incomes
	Farm income	value of annual crop production and livestock income (sales and products)
	Off-farm income	value of annual off-farm income, includes enterprise income, wage employments, and salaried jobs, income from rents, remittances, gifts, pensions, inheritance, and sales of assets and lottery
Asset	Tropical livestock units (TLUs)	measured as per Storck et al. (1991)
	Asset index	based on a PCA score of 34 asset items, normalized
	Housing index	based on a PCA score of 12 housing characteristics, normalized
	Land	in hectares
Shock	Shock index	Absolute mean deviation of rainfall in the wettest quarter of the year in mm.
Small town dweller		1 if household resides in a small rural town

Note: For the factor variables, 0 constitutes the base category; all variables are aggregated at household level except village consumption; and consumption, income, and asset variables are deflated by AEUs except for the two asset indices.

Income data is available as income from sale of own crops (cereals, roots, and trees included) production, sale of livestock and livestock products, household enterprise income, and wage income (including casual labor income and income from PSNP employment). The farm income variable is given as a sum of income from sale of own production of crops, livestock, and livestock products. Off-farm income is calculated as income from household enterprises and wages. Consumption, income, and asset variables were converted to their natural logarithms by adding one to their series to avoid missing values for zero values.

4. Results and discussion

4.1. Summary statistics

Household characteristics of for the study sample are given in Table 3.3. Among the households sampled in this study 26 percent were headed by women. The share of households with a single member was 4 percent. Nearly 65 percent of the household heads were illiterate with no form of education. Just above 15 percent had attained basic primary level education enabling them to acquire just literacy and numeracy skills. Another 15 percent had attained the general primary level. A combined share of about 12 percent of the households were headed by individuals with general primary level (maximum level attained was Grade 8) of education. Household heads who had attained at least the general secondary level of education made up 6 percent of the total. These educational levels together translate

[31] Leave out mean.

into 2.11 years of schooling for an average household head. This suggests that heads' literacy levels failed to cover even the basic skills of literacy and numeracy (that is, basic primary education) on average. Household heads were older than the average age of their households by about 23 years. This is indicative that there were many young members in the households. The mean number of male household members was slightly higher than females in the households.

Summary statistics of household consumption and income along with other household resources are given in Table 3.4. The mean household food consumption was markedly higher than non-food consumption – about 80 percent of total consumption as is typical of households in sub-Saharan Africa (Bachewe et al., 2016). Mean off-farm incomes per capita were also higher than farm incomes but they also had higher standard deviations. This indicates that off-farm incomes were an important component of household incomes. Off-farm incomes were more unevenly distributed as compared to farm incomes. The average livestock owned by a household was 2.94 TLUs. This is equivalent to about three cows or two oxen and a donkey. This is indicative of the importance of livestock assets for households. The average land size owned by a household was 1.24 hectares. This is above national averages (Dorosh & Rashid, 2013) mainly because it is not measured as cultivated land (that is, farm size) but as land owned including cultivated and rented land in addition to land lived on. Another important summary statistic is that the village averages for both total consumption and income were higher than the household averages. This is a precursor to a potential positive spillover at the village level.

Table 3.3. Summary statistics – household demographics and education levels

Variable	All waves (N = 9,750)		2011/12 (n = 3,250)		2013/14 (n = 3,250)		2015/16 (n = 3,250)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Sex, head (F=1)	0.26	-	0.25	-	0.26	-	0.27	-
Single member household (=1)	0.96	-	0.94	-	0.96	-	0.97	-
Level of education, head								
No education	0.64	-	0.64	-	0.65	-	0.64	-
Basic primary (1-4)	0.15	-	0.16	-	0.15	-	0.14	-
General primary (5-8)	0.12	-	0.12	-	0.12	-	0.13	-
General secondary (9-10)	0.03	-	0.03	-	0.03	-	0.03	-
Preparatory (11-12)	0.01	-	0.01	-	0.01	-	0.01	-
Undergraduate	0.04	-	0.03	-	0.03	-	0.04	-
Post-graduate	0.00	-	0.00	-	0.00	-	0.00	-
Schooling years, head	2.11	3.63	2.05	3.53	2.07	3.61	2.20	3.74
Cumulative school years, household	9.66	10.38	8.76	10.07	9.64	10.19	10.60	10.80
Age, head	46.12	15.44	44.54	15.60	46.10	15.29	47.70	15.27
Mean age, household	23.14	11.77	24.17	12.40	23.65	11.53	21.60	11.20
Males	2.71	1.68	2.48	1.58	2.77	1.67	2.88	1.76
Females	2.69	1.50	2.46	1.41	2.76	1.50	2.87	1.57
Dependents	2.95	1.90	2.50	1.72	2.85	1.80	3.52	2.03
Dependency ratio	50.29	23.27	46.75	24.50	48.47	22.77	55.65	21.48
Small town dweller	0.12	0.32	0.12	0.32	0.12	0.32	0.12	0.32
Adult equivalent units	4.30	1.95	3.86	1.81	4.38	1.95	4.66	2.01
Household size	5.56	2.52	4.94	2.32	5.60	2.47	6.13	2.63

Source: Author's calculations using ESS data from 2011/12, 2013/14 and 2015/16 waves

Table 3.4. Summary Statistics – households' consumption, income, and assets

Variables	All waves (N=9,750)		2011/12 (n=3,250)		2013/14 (n=3,250)		2015/16 (n=3,250)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Village consumption, total	9,312.23	8,439.33	10,219.18	10,698.90	8,800.86	6,976.45	8,912.41	7,008.31
Household consumption, total	5,249.48	5,049.97	5,542.34	6,672.47	5,019.56	3,809.06	5,186.52	4,165.18
Food consumption	4,158.95	3,931.30	4,485.25	4,970.85	3,912.45	3,138.15	4,079.16	3,412.32
Non-food consumption	1,090.52	2,595.12	1,057.09	4,072.31	1,107.12	1,330.12	1,107.36	1,361.46
Village income, total	14,942.00	65,144.89	9,387.11	24,204.55	14,336.72	31,900.12	21,102.16	105,173.72
Household income, total	6,536.11	44,378.88	4,615.97	24,636.48	6,288.20	19,148.33	8,704.15	70,196.87
Farm income	1,787.97	7,204.74	762.96	3,784.13	2,435.97	8,739.17	2,164.98	7,965.61
Off-farm income	4,748.14	43,777.69	3,853.01	24,388.52	3,852.23	30	6,539.17	69,704.42
Livestock, TLU	2.94	4.42	2.53	4.39	2.80	4.14	3.47	4.66
Asset index	0.07	0.08	0.03	0.09	0.08	0.06	0.12	0.07
Housing index	0.25	0.16	0.24	0.18	0.25	0.15	0.25	0.14
Land owned	1.24	5.32	1.08	2.35	1.35	4.43	1.29	7.73
Shock index	0.81	0.59	0.81	0.58	0.80	0.59	0.80	0.60

Note: All variables are either on an annual basis or expanded to their annual equivalent to have a similar time scale; consumption, income, and TLUs are given as age-sex adjusted quantities.

Source: Author's calculations using ESS data from 2011/12, 2013/14 and 2015/16 waves

4.2. Heterogeneity and variability in consumption, income, and assets

Households in the study sub-sample exhibited marked heterogeneity in terms of place of residence, literacy, gender, and whether a household had a single member. Table 3.5 gives the differences in mean consumption, incomes, and asset holdings by selected categories. The results show that rural households' total consumption was quite different from that of households living in small towns. Households which belonged to small towns consumed ETB 1,545.27 more than the rural households. A closer look shows that the chunk of this difference came from non-food consumption (ETB -1,071.46). Small town dwellers also consumed ETB -473.81 (t-stat. = 16.95) more on food items. On the income side, small town dwellers earned ETB 8,219.96 more income than their urban counterparts. Quite a large share of this income differential came from farm incomes (ETB -9,415.32). The two groups showed a statistically significant difference in terms of off-farm incomes where households in small towns had ETB -9,415.32 more off-farm incomes. In terms of assets, rural households scored better in livestock and landholdings while small town dwellers had better asset and housing conditions.

Table 3.5. Mean comparison of consumption, incomes, and assets by selected categories

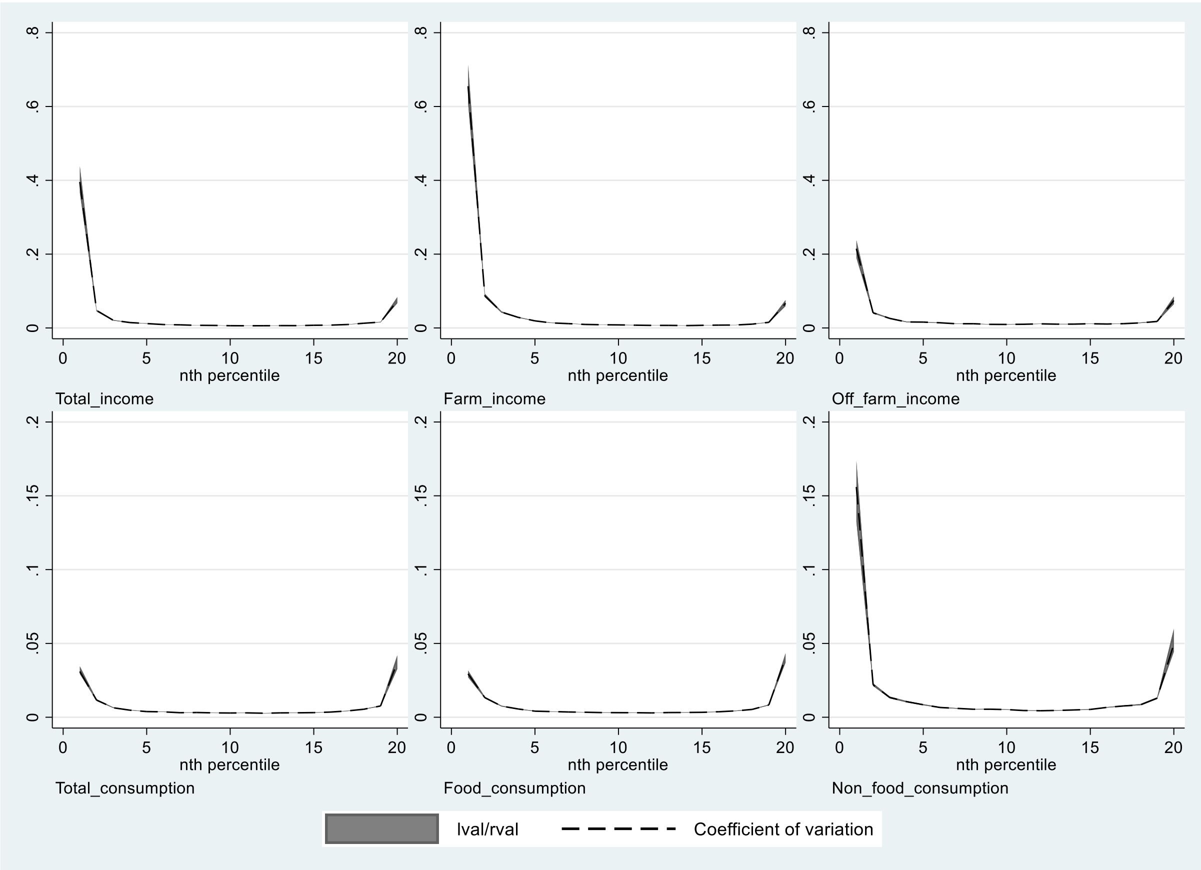
Variables		Rural-small town		Literate-illiterate		Male-female		Single- not membered	
		Difference		Difference		Difference		Difference	
	Land owned	1.08	**	-0.16		0.79	**	-1.00	**
		(0.17)		(0.11)		(0.12)		(0.26)	
	Livestock, TLU	2.34	**	-0.52	**	1.61	**	-2.77	**
		(0.14)		(0.09)		(0.10)		(0.22)	
	Asset index	-0.07	**	0.03	**	0.00		-0.02	**
		(0.00)		(0.00)		(0.00)		(0.00)	
	Housing index	-0.26	**	0.10	**	0.01		0.02	**
		(0.00)		(0.00)		(0.00)		(0.01)	
Consumption	Food	-473.81	**	446.88	**	-336.55	**	2,656.50	**
		(123.68)		(82.90)		(91.03)		(193.36)	
	Non-food	-1,071.46	**	620.00	**	-122.46	**	1,262.90	**
		(80.98)		(54.44)		(60.15)		(128.23)	
	Total	-1,545.27	**	1,066.88	**	-459.01	**	3,919.40	**
		(158.22)		(106.10)		(116.94)		(247.61)	
Income	Farm income	1,031.80	**	640.62	**	711.48	**	-591.32	
		(276.06)		(167.68)		(186.78)		(481.79)	
	Off-farm	-9,415.32	**	4,055.80	**	796.11		8,179.17	**
		(1,374.95)		(923.60)		(1,014.85)		(2,172.36)	
	Total	-8,219.96	**	4,533.25	**	1,581.10		7,168.58	**
		(1,394.70)		(936.08)		(1,028.68)		(2,202.59)	
% share, base group		88.2		35.86		74.15		4.35	
N		9,750		9,750		9,729		9,750	

Note: ** p<0.05; standard errors in parenthesis.

Source: Author's calculations using ESS data from 2011/12, 2013/14 and 2015/16 waves.

With regard to literacy, there is a statistically significant difference in consumption, incomes, and assets except for land ownership. Households with literate heads out-consumed (ETB 446.88) and out-earned (ETB 640.62) illiterate households. They also had better asset and housing conditions. Households with illiterate heads owned more livestock (0.52 TLUs).

In terms of household head's gender, surprisingly female headed households consumed (ETB 459.01) more than male headed households. And this is true both for food (ETB 336.55) and non-food (ETB 122.46) consumption. Male headed households earned ETB 711.48 more farm incomes than female headed households though the difference was insignificant for incomes as a whole. Male headed households owned more land (0.79) and livestock (1.61 TLUs) than female headed households. The difference in housing and other assets ownership was statistically indistinguishable between male and female headed households. The results that male headed households outperformed female headed households in terms of farm incomes, land, and livestock ownership are consistent with literature (Dorosh & Rashid, 2013).



Source: author's construction using ESS data from 2011/12, 2013/14 and 2015/16 waves

Figure 3.1. Coefficients of variations of consumption and income by 20th consumption percentiles

Another important dimension explored in this study is the variability of consumption and income. Figure 3.1 gives a graph of the coefficients of variations (CV) for each of the five consumption quintiles with respective 95 percent confidence intervals. The graphs in the first row show income and in the second row they show consumption. Looking at the CVs plotted vertically, household incomes are more volatile than consumption, and this volatility is more pronounced at the extremes of the distribution for both income and consumption. Non-food consumption is more volatile than food consumption and farm income is more volatile than non-farm income.

4.3. Co-movements

Evidence of a possible smoothing behavior is a strong co-movement of household and village level consumption and incomes. Table 3.6 gives the correlation coefficients of household and village level variables. The higher correlation coefficients show a stronger co-movement of household variables with community level variables. A look at the correlation coefficients of total household consumption with village level consumption, income, and asset variables shows that the strongest correlation was between household consumption and its village average (ρ =73.6 percent) and village averaged food consumption (ρ =72.1 percent). This is mainly because a large share (80 percent, refer to Table 3.4) of household consumption is food consumption. Household food consumption follows a path similar to total household consumption. Household non-food consumption also has a relatively strong correlation with village level consumption (ρ = 25.6 percent).

On the other hand, total income (ρ = 17.2 percent) and off-farm income (ρ = 10.2 percent) have small correlation coefficients with farm income while livestock owned and land owned had no statistically discernible correlations with farm income. There is some degree of correlation between livestock ownership and land ownership with their corresponding village level means. This, in turn, is indicative of potential asset smoothing behavior at the village level. These results imply that household consumption and other household covariates tend to co-move with their respective village averages but not much with the village averages of the other variables.

Another important observation can be made about households' diversification drives from Table 3.6. A quick look at the upper half of Table 3.6 shows that households' consumption is highly correlated to their food consumption (ρ = 97.1 percent). This defines the level of poverty of an average household and the nature of subsistence in rural Ethiopia (Baye, 2017; Dorosh & Rashid, 2013). Household incomes are strongly correlated with both farm (ρ = 35.6 percent) and non-farm (ρ = 92.2 percent) incomes and more so with non-farm incomes.

Table 3.6. Correlation coefficients (ρ) of household and community level variables

	Household level							
	Income			Consumption				
	Off-farm	Farm	Total	Total	Food	Non-food	Land owned	Livestock
Household level								
Off-farm income	1							
Farm income	-0.034	1						
Total income	0.922	0.356	1					
Total consumption	0.212	0.115	0.243	1				
Food consumption	0.152	0.106	0.183	0.971	1			
Non-food consumption	0.307	0.085	0.320	0.575	0.363	1		
Land owned	-0.064	0.133	-	-0.037	-0.037	-	1	
Livestock	-0.090	0.072	-0.056	-	-	-0.048	0.155	1
Village level								
Total consumption	0.160	0.067	0.176	0.736	0.721	0.402	-0.084	-0.100
Food consumption	0.052	0.074	0.077	0.575	0.613	0.143	-	0.130
Non-food consumption	0.186	0.068	0.201	0.256	0.143	0.508	0.035	-
Total income	0.579	0.112	0.585	0.172	0.145	0.177	-0.028	-0.056
Farm income	-	0.585	0.220	-		0.030	0.062	0.060
Off-farm income	0.600	-	0.563	0.102	0.081	0.120	-0.030	-0.043
Livestock	-0.054	-	-0.043	-	-	-0.042	0.100	0.660
Land owned	-0.032	0.078	-	-	-	-	0.441	0.046

Note: All reported correlation coefficients are significant at p>0.05 and entries with "-" are insignificant and are not different from 0; N = 9,750.

Source: Author's calculations using ESS data from 2011/12, 2013/14 and 2015/16 waves.

4.4. Econometric results

This sub-section contrasts the estimates obtained from the regression coefficients using the FE-2SLS estimation. Table 3.7 gives the results for two different cases. One is household fixed effects regressions where households are risk pooling agents and the village is community aggregation at which the risk is pooled. The other is a fixed effects regression where villages are the risk pooling agents and the woreda is the risk pooling community aggregation. In each case, within and between coefficients are reported for income and asset variables. Following literature on consumption smoothing, the contrast estimator is constructed using total income as the covariate of interest. Specific to the other objective of this study, income is disaggregated into farm and off-farm incomes and another contrast estimate is done using the coefficients of off-farm income. All regressions are controlled for socio-demographic and educational background of the households; however, only variables associated with household incomes and assets are reported for brevity.

The household wide variables used as instruments passed the inclusion and exclusion restriction tests of instrument validity. A correlation table (Appendix 3.1) of the instruments, the endogenous variable (income) and the dependent variable (consumption) shows that the instruments are correlated with income and not so much with consumption. The test for endogeneity was run both on the pooled sample and for each of the three waves. The null hypothesis of exogenous income was rejected for the pooled sample and for the second and third waves. A test for weak instruments both for the pooled data and for each round indicated that the instrumentation in this study passed the exclusion criteria. A null hypothesis of weak instruments is rejected. The results are reported in Appendix 3.2. A more formal test for weak instruments in both the aggregated and disaggregated income regressions confirms that the instruments used were not weak with the Cragg-Donald Wald statistic well over the respective 5 percent instrumental variable bias critical value.

For the contrast estimate to be significant either the within or the between or both the income coefficients should be statistically significant. Moreover, the within estimate has to be smaller than the between estimate for the presence of a potential positive spillover to exist since the between estimate is the source of synergy that represents insurance for a household. A quick look at Table 3.7 shows that the contrast estimators for household regressions are not statistically different from one. This result means that the complete insurance hypothesis holds for households in rural Ethiopia. In other words, households fully insure their consumption against shocks by pooling risks at the village level. The first block of Table 3.7 gives the results for households as risk pooling agents at the village level. The FE-2SLS procedure is run for both the within and between regressions and for cases where income is aggregated and where it is disaggregated into farm and off-farm incomes.

Picking up on the aggregated income case (Columns 1 and 2 in Table 3.7), the within coefficient of the income variable is statistically significant ($\hat{\delta}^W$ = 0.023 (s.e. = 0.012)) and the between effects coefficient of income is insignificant ($\hat{\delta}^B$ = -0.021 (s.e. 0.011)). The resulting contrast estimate, $\hat{\beta}$, is not significantly different from unity. A direct test of the contrast estimator, $\left(1-\delta^W/\delta^B\right)$, reported in Table 3.7 shows that $\hat{\beta}$ is not statistically different from one ($\hat{\beta}$ = -0.071 (-2.903, 1.205)).

The second objective of this study is addressed in the columns where income is disaggregated. The disaggregation of income into farm and off-farm incomes enables estimating the within and between coefficients of the off-farm income variable. The results of the household FE-2SLS regression reported in Table 3.7 (Columns 3 and 4) show that the within coefficient was not statistically different from zero ($\hat{\delta}^W$ = 0.007 (s.e. = 0.0017) while the between coefficient was significant ($\hat{\delta}^B$ = -0.128 (s.e. = -0.018)) at the 95 percent confidence level. A zero within coefficient estimate suggests there is complete risk pooling. A test of the contrast estimator, $\hat{\beta}$, constructed using these two coefficients was not statistically different from one ($\hat{\beta}$ = -0.294 (-2.117, 2.782). Therefore, this result signals that households fully smoothened their consumption through pooling consumption risks at the village level by means of off-farm incomes. Whether total income or off-farm income is considered to arrive at the contrast estimator, the result of full risk pooling has a striking implication. Even when the key assumptions of perfect insurance and credit markets of the full insurance model did not hold, households managed to achieve complete consumption smoothening by devising efficient informal insurance alternatives. Though the results of previous studies (Suri, 2003; Townsend, 1994), mostly reject complete smoothing, they support the claim that households operate close to full smoothing. It is worth noting that constructing a contrast estimate using covariates other than income could lead to smoothing outcomes other than complete smoothing.

The other block (Columns 7-10) in Table 3.7 report FE regression results where villages are the agents pooling risks at the woreda level. The last block of regressions is useful for testing the presence of higher level risk pooling – risk pooling by villages at the woreda level. In running these sets of regressions, the study followed an informal way of addressing the measurement error in income. Instead of instrumenting income, averaging eliminates some of the noise in the income variables. The hope is that the measurement errors are greatly mitigated in the averages (Suri, 2003). The same instruments used in the previous two blocks were weak, and as a result we resorted to this less formal approach where averaging variables, particularly income, took care of endogeneity due to income measurement errors. The results signal that villages, taken as rationally operating aggregations, tend to smooth their consumption against short term shocks by pooling their resources, namely incomes, at the woreda level. In other words, the complete insurance hypothesis holds at a higher level of aggregation as well, though both formal and informal mechanisms are not as well documented in literature. Looking at the case where income is aggregated, the contrast estimate constructed from the within and between coefficients of the fixed effects regressions, $\hat{\beta}$, are not significantly different from unity ($\hat{\beta}$ = 1.000 (0.297, 1.184)). For the case where income is disaggregated into farm and off-farm income the contrast estimate ($\hat{\beta}$ = 1.000 (0.297, 1.184)) is not statistically different from one. In other words, the ratio of the within to the between effects coefficients is not statistically different from zero.

The results reported in Table 3.7 do not account for the heterogeneity in consumption in the study sub-sample. To address this, the sub-sample was divided into consumption quintiles. For each quintile, a FE-2SLS regression was used to account for endogeneity of income to study household risk pooling behavior. To correct endogeneity in the village regressions, averaging was used as an informal fix for income endogeneity. These results are reported in Table 3.8. Contrast estimates were calculated both for the case where households pooled risks at the village level and where villages pooled risks at the woreda level. These contrast estimates were calculated for each quintile. The upper half of Table 3.8 gives the contrast estimate results where income is observed as total income. The lower half, on the other hand, gives contrast estimate calculations based on the within and between coefficients of regression for the off-farm income variable. These contrast estimators for the household level regressions, should be interpreted with caution as the bias of instrumentation can go up to as high as 20 percent (see Appendix 3.2).

Table 3.7. Contrast estimator: FE-2SLS results for within and between regressions for ln(total consumption)

Variables	Household				Village			
	Within	Between	Within	Between	Within	Between	within	Between
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total income	0.023*	0.021*	-	-	0.007	0.128***	-	-
	(0.012)	(0.011)			(0.017)	(0.018)		
Farm income	-	-	0.006	-0.003	-	-	-0.016	0.018
			(0.007)	(0.006)			(0.011)	(0.011)
Off-farm income	-	-	0.007*	0.005*	-	-	0.023*	0.065***
			(0.004)	(0.003)			(0.012)	(0.011)
Livestock	0.087***	0.138***	0.113***	0.158***	0.115***	0.153***	0.125***	0.162***
	(0.021)	(0.014)	(0.020)	(0.015)	(0.044)	(0.032)	(0.045)	(0.034)
Asset index	-0.074	0.726***	-0.113	0.697***	-0.464	0.901	-0.522	0.991
	(0.175)	(0.227)	(0.188)	(0.234)	(0.569)	(0.782)	(0.558)	(0.765)
Housing index	0.354***	0.828***	0.410***	0.852***	0.286	0.100	0.325	0.574**
	(0.105)	(0.078)	(0.110)	(0.079)	(0.267)	(0.263)	(0.284)	(0.273)
Land owned	0.012	0.062***	0.024	0.085***	-0.064*	-0.085**	-0.058*	-0.067*
	(0.023)	(0.019)	(0.022)	(0.020)	(0.033)	(0.035)	(0.032)	(0.036)
Observations	9,628	9,629	8,667	8,786	993	993	972	972
R-squared	0.044	0.189	0.047	0.167	0.745	0.283	0.750	0.269
F statistics	7.974		7.228	42.98	1.821	13.04	1.789	11.51
Contrast estimate	-0.071		-0.294		1.000		1.000	
	(-2.903, 1.205)		(-2.117, 2.782)		(0.297, 1.184)		(0.297,1.184)	

Note: Income variables, livestock, and land are transformed into their natural logarithms.
Standard errors in parenthesis and clustered at the household and woreda levels respectively; CIs for contrast estimates (CIs) are bootstrapped at 100 reps; *** p<0.01, ** p<0.05, and * p<0.1.

Source: Author's calculations using ESS data from 2011/12, 2013/14 and 2015/16 waves

The results presented in Table 3.8 show that the complete insurance hypothesis holds for both households and villages. Looking at the first half of the table, the contrast estimates are not statistically different from zero for each quintile of the households for village regressions. Therefore, irrespective of the quintile to which they belong, households fully smooth their consumption by pooling resources (income in this case) at the village level and villages at the woreda level. Looking at the lower half of Table 3.8, off-farm incomes, rather than total incomes, are used for constructing the contrast estimates. The contrast estimates show the same pattern here as well. None of them are statistically and significantly different from one. What this means is that households, irrespective of the consumption quintile they fall in, fully smooth their consumption by pooling their resources (off-farm incomes in this case) at the village level. In the same way, villages, irrespective of the consumption quintile in which they fall, fully smooth their consumption by pooling their resources at the woreda level.

Table 3.8. Contrast estimates based on FE regression results of within and between regressions for consumption

Risk pooling		Quintile				
		1	2	3	4	5
Contrast estimates based on total income						
Households in village	$\hat{\beta}$	-0.892	3.281	2.581	1.882	-0.703
		(-56.39, 3.42)	(-1.27, 39.47)	(-0.03, 41.24)	(0.33, 24.03)	(-26.45, 0.55)
	Obs.	2,091	2,076	2,078	2,087	2,070
	Grps.	703	703	702	703	702
Villages in Woredas	$\hat{\beta}$	1.727	0.714	11.038	1.505	1.244
		(0.46, 56.42)	(-190.89, 3.85)	(6.35, 85.83)	(0.40, 5.82)	(-1.43, 19.34)
	Obs.	198	195	195	195	195
	Grps.	66	65	65	65	65
Contrast estimates based on Off-farm income						
Households in village	$\hat{\beta}$	5.606	1.502	1.839	2.486	0.577
		(2.85, 44.12)	(-3.34, 33.67)	(0.68, 15.81)	(0.66, 342.53)	(-3.99, 18.94)
	Obs.	2,091	2,076	2,078	2,087	2,070
	Grps.	703	703	702	703	702
Villages in Woredas	$\hat{\beta}$	0.172	2.456	1.73	-2.871	1.063
		(-53.13, 3.48)	(-0.99, 27.63)	(-0.08, 6.04)	(-100.57, -0.62)	(-0.86, -0.62)
	Obs.	198	195	195	195	195
	Grps.	66	65	65	65	65

Note: Robust standard errors in parenthesis; standard errors are clustered by woreda; R^2 are centered; the CIs are bootstrapped at 100 replications.

Source: Author's calculations using ESS data from 2011/12, 2013/14 and 2015/16 waves

5. Conclusion and recommendations

This study tried to understand households' risk pooing behavior in rural Ethiopia in terms of household incomes in general and off-farm incomes in particular. Although theory stipulates that households should fully smooth consumption by pooling idiosyncratic risks at the village level (or some other aggregation), the jury on this assertion is still out as there is no empirical consensus on complete consumption smoothing. This study applied a less frequented methodological approach for testing the complete insurance model – the contrast estimator anchored on peer effects literature. In pursuing the study's objectives, three waves of the Ethiopian Socioeconomic Survey (ESS) were used. The sub-sample for the study followed 3,250 households for three rounds in 331 villages in 260 woredas. The study used the following categories of variables: demographic and education, consumption, income, assets and shocks.

Data shows that household consumption was dominated by income, and around 80 percent of household consumption was food. Off-farm incomes were more than farm incomes, but they were also more volatile. An average household in our sub-sample owned nearly three cows and 1.24 hectares of land. Village averages of both household consumption and income were higher than household averages setting the stage for a possible source of village spillovers out of which consumption smoothing can occur. Households exhibited marked heterogeneity and variability in terms of their consumption and incomes. There was a marked difference between households' consumption, incomes, and assets along rural-urban, literate-illiterate, and gender divides. In terms of variability, consumption was found to be less volatile than income. The study also explored the co-movement of household level consumption, incomes, and assets in relation to their village averages. Total consumption co-moved with its village average 74 percent of the time. Total household income co-moved with its village average 58 percent of the time. These correlations lend supporting evidence for the existence of potential consumption smoothing through risk pooling at the village level.

In the subsequent econometric analyses, the study tested the full insurance hypothesis based on Suri's (2003) formulation of the contrast estimator both for households in villages and villages in woredas. For the household regressions, the problem of endogeneity coming from the reflection problem was automatically addressed by using the contrast estimator, and that coming from the error in measurement of income was addressed by instrumenting income using household wide variables. For the village regressions, the endogeneity arising from measurement errors in income was addressed less formally by relying on the idea that this averaging eliminated some of the measurement errors (noise) in income as the same instruments used in the household regressions ended up being weak in the village regressions. In addition to computing contrast estimates for the whole study sub-sample, the study also looked at contrast estimates for consumption quintiles. The results of the econometric analyses showed that households were quite resilient to idiosyncratic shocks. The results of this study also show that even in the absence or highly fragmented formal insurance mechanisms, households used risk pooling at the village level to mitigate idiosyncratic shocks. Though the results for risk pooling by villages at the woreda level should be seen with caution, they suggest that villages are also quite resilient to village level idiosyncratic shocks. Further, testing the consumption smoothing behavior of households by consumption quintiles showed that despite the heterogeneity among the quintiles, the complete insurance hypothesis was not rejected irrespective of the consumption quintiles.

The finding that households are resilient against short term consumption shocks even in the absence of formal insurance and credit facilities (which when available are fragmented) has important implications for policy interventions aimed at improving rural household welfare. A key takeaway is that such policies should not be targeted at relieving households of the short-term idiosyncratic shocks that they face. Instead, these policies should focus on correlated risks that are common to all households in a given village or perhaps a higher level of aggregation where the informal social networks that enable risk pooling break down. Another lesson that can be learned is that since households can do quite an efficient job of addressing household level short term idiosyncratic shocks, it is best to leave these to them. This will make available resources that can be invested in long term threats to household welfare such as desertification, malnutrition, urbanization, land fragmentation, and industrialization. For example, governments and other developmental agencies should focus less on emergency relief efforts such as food distribution during famines. Another case is the Productive Safety Net Program (PSNP). Given the results of this study, PSNP should devote less resources for short-term idiosyncratic welfare shocks as households are quite efficient in handling these on their own. A better way of investing would be strengthening informal social networks through which households aggregate short term idiosyncratic risks to the village level. The finding that villages fully pool risks at the woreda level, is suggestive that the lowest level of aggregation at which welfare improving interventions should be aimed is likely to be higher than the woreda level. However, this last result should be interpreted with caution.

In this study income was assumed to be the channel, the key resource, through which consumption smoothing was achieved. Given this assumption, the full insurance hypothesis held whether the resource was taken to be total household income or just rural off-farm income. This result clearly shows that off-farm incomes play a key role in consumption smoothing of households and villages.

Despite the key insights into welfare of households that this study provides, a lot remains to be understood about household welfare and consumption smoothing. In particular, the results of this study can be improved or extended by addressing the following points. First, this study is exclusively focused on consumption smoothing, but other studies show that households may resort to other forms of smoothing. One possibility discussed by Berloffa and Modena (2013) is that households may resort to asset smoothing below a certain income threshold. It would be fitting to see if such a trade-off exists among households in rural Ethiopia. Second, throughout the study the risk pooling aggregations are defined based on geography – villages for households and woredas for villages. However, there are plenty of indications in literature that risks may be pooled along kin, racial, and cast lines or in religious groups. It would be useful for policy to see if consumption smoothing is achieved along these lines and if so to what extent. Third, the current study looks at risk pooling without referring to specific social networking mechanisms through which this pooling is achieved. Perhaps future studies can explore specific social networking mechanisms. This will give welfare interventions a clearer picture of how these specific informal insurance mechanisms can best be supported. Finally, this study uses annualized data which hides seasonal dynamics of household consumption smoothing. Future data collection should envision more than one round of visits to households within a year to study the fluctuations in consumption smoothening between peak and slack production seasons.

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Appendix 3

Appendix 3.1. Correlation Table of Instruments with consumption and income

		Total consumption	Income			Schooling					Household size
			Total	Farm	Off-farm	cummulative	Highest level	Dependents	Males	Age	
Total consumption		1									
Income	Total	0.0371***	1								
	Farm	0.0383***	0.654***	1							
	Off-farm	-0.0513***	0.417***	-0.181***	1						
Schooling	cummulative	0.0667***	0.0819***	-0.0381**	0.142***	1					
	Highest level	0.0826***	0.108***	-0.0804**	0.191***	0.817***	1				
Dependents		-0.136***	0.0873***	0.199***	-0.0445**	0.115***	0.0162*	1			
Males		-0.114***	0.146***	0.224***	-0.0115	0.312***	0.173***	0.561***	1		
Age		-0.127***	0.0160*	0.133***	-0.0722**	0.366***	0.187***	0.378***	0.585***	1	
Household size		-0.125***	0.163***	0.255***	-0.0133	0.390***	0.217***	0.721***	0.776***	0.689***	1

N.B. The variables are contstructed for household members not the heads of households

* for p<0.10,** p<0.05, ***p<0.01

Source: author's calculation using ESS data

Appendix 3.2. Test for endogeneity, weak instruments, and over-identifying restrictions

	Test for Endogeneity			Weak instrument tests			Test for over-identifying restrictions		
	Ho: variables are exogenous			Ho: Instruments are weak					
		Statistic	P-value		Statistic	Critical value		Statistic	p-value
Round 1	Durbin (score)	0.092	0.762	Partial R^2	0.534	-	Sargan (score)	60.16	0.000
	Wu-Hausman	0.091	0.762	F(12,3429)	327.784	21.01	Basmann	60.68	0.000
Round 2	Durbin (score)	11.179	0.001	Partial R^2	0.261		Sargan (score)	53.05	0.000
	Wu-Hausman	11.144	0.001	F(12,3429)	93.288	21.10	Basmann	53.36	0.000
Round 3	Durbin (score)	21.433	0.000	Partial R^2	0.265		Sargan (score)	26.39	0.009
	Wu-Hausman	21.430	0.000	F(12,3429)	95.163	21.10	Basmann	26.34	0.010
Pooled	Durbin (score)	12.158	0.001	Partial R^2	0.370		Sargan (score)	114.20	0.000
	Wu-Hausman	12.147	0.001	F(12,3429)	468.684	21.10	Basmann	115.10	0.000

Source: author's calculation using ESS data

Appendix 3.3. Townsend type regression results

VARIABLES	Dependent: Consumption	Dependent: Consumption	Dependent: Demeaned consumption
Village consumption	0.756***	0.763***	
	(0.018)	(0.015)	
Total income	-	0.013***	-0.005
		(0.003)	(0.006)
Livestock	-	0.022**	0.039
		(0.011)	(0.025)
Asset index	-	0.061	0.084
		(0.092)	(0.198)
Housing index	-	0.187***	0.069
		(0.056)	(0.118)
Land owned	-	0.000	0.044
		(0.013)	(0.030)
Wave 2	0.027***	0.000	-0.037
	(0.010)	(0.011)	(0.025)
Wave 3	0.034***	0.012	0.031
	(0.012)	(0.015)	(0.032)
Constant	1.518***	1.101***	9.413***
	(0.160)	(0.171)	(0.228)
Observations	8,800	8,691	8,691
R-squared	0.518	0.505	0.066
Number of households	3,229	3,228	3,228

Note: Robust standard errors in parenthesis, clustered at the village level; *** p<0.01, ** p<0.05, and * p<0.1.

Source: Author's calculations using ESS data.

Appendix 3.4. Hausman test for fixed or random effects models for unweighted full sample household regressions

chi^2	P-value
238.33	0.000

Ho: Difference in coefficients is not systematic

Chapter Four: Multidimensional Poverty, Vulnerability, and the Role of Off-farm Participation in Rural Ethiopia

(Paper 3)

Abstract

With economic growth and development, the share of agriculture in a country's economy is bound to decline. Hence, growth policies must consider alternative sources of income and employment. This study examines whether off-farm activity participation has any material impact on rural Ethiopian households' multidimensional poverty and vulnerability. It uses three waves of panel data from the Ethiopian Socioeconomic Survey spanning five years. It uses a combination of matching and difference-in-difference (DID) techniques to study off-farm activities impact. The results show that participation in small family businesses or permanent wage employment reduce multidimensional poverty but not vulnerability to multidimensional poverty. There are also indications that the impact of participation in off-farm activities varies based on a household's position in the multidimensional poverty spectrum. For example, employment as casual laborer or being employed in the Productive Safety Net Program (PSNP) has an impact on a household's odds of being multidimensionally poor for the poorest households. The study recommends that off-farm activity participation should be encouraged for reducing multidimensional poverty. Vulnerability to multidimensional poverty, however, does not respond to such participation and hence other avenues need to be considered for improving the households' future welfare prospects.

Keywords: Off-farm activities; multidimensional poverty; vulnerability to poverty; welfare

JEL Classification Codes: I31; J43; O13; Q12

1. Introduction

The importance of agriculture is bound to decline with economic growth (Chenery et al., 1975). This structural shift is accompanied by the increasing importance of the non-agricultural sector. Studies show that households in sub-Saharan African (SSA) countries get about 35 percent of their incomes from off-farm income generating activities (Barrettet al., 2001; Davis et al., 2017; Haggblade et al., 2010; Yeboah & Jayne, 2018). In Ethiopia, more than half of rural households participate in non-farm activities (Bezu et al., 2012).

Despite sizeable empirical literature documenting the importance of off-farm income generating activities, scant attention has been paid to it in national growth and development policies and strategies in Ethiopia. The Agricultural and Rural Development Policy (MoA, 2003) largely avoids any substantive discussion on supporting rural off-farm income generating activities. The Growth and Transformation Plans (GTPs) makes only a passing mention of off-farm income generating activities (MoFED, 2010, 2015). The off-farm sector, however, is projected to be the fastest growing source of employment and it is expected to absorb a good number of unskilled young people (Filmer & Fox, 2014).

It is argued that multidimensional welfare measures are superior to indirect or unidimensional measures (Atkinson, 2003; Sen, 1976). However, existing studies use income or consumption expenditure as a proxy for household welfare or pick one aspect of welfare such as food security (Owusu et al., 2011) for a detailed study. There are very few studies that directly look at household welfare using multiple dimensions and even fewer studies that look at the effects of off-farm participation. Studies that explore the effects of off-farm participation on household welfare do not look at its effect on future multidimensional poverty even though such studies add insights to welfare dynamics (Azeem et al., 2018).

This study builds on advancements in welfare and poverty literature (Alkire & Foster, 2011; Calvo & Dercon, 2005; Costa et al., 2018; Dehury & Mohanty, 2017) by examining how off-farm participation affects multidimensional poverty and vulnerability.

Various development reports show that Ethiopia has made remarkable strides in poverty reduction, but the share of the poor is still very high in the country. For example, between 2000 and 2011 the poverty headcount fell by 14 percentage points from 44 to 30 percent and further to 23.5 percent in 2016 (Stifel & Woldehanna, 2016; UNDP Ethiopia, 2018). However, these figures hide the multidimensional nature of poverty and vulnerability. According to estimates for 2015, 36.3 percent people were living below the \$1.90 a day poverty line. This figure jumped to 76.2 percent when the poverty line was moved up to \$3.10 a day (The World Bank, 2017). A 2016 estimate found that 83.6 percent of the population (or 86 million people) were poor as per the multidimensional poverty index (MPI). These figures necessitate a study of poverty and vulnerability using a multidimensional perspective.

This study contributes to a better understanding of household poverty and vulnerability and the effects that off-farm participation has in a number of novel ways. First, it analyzes the impact that participating in off-farm income generating activities has on household multidimensional poverty and vulnerability within the same framework using the same data. Second, the study uses MPI to measure poverty. Measuring household vulnerability using MPI distribution is another contribution of this study to literature. This study closely follows Costa et al. (2018) but uses households as the unit of analysis and reduces the vulnerability categories to two emphasizing on only a jump in the MPI position. This approach is superior to that used by Chaudhuri et al. (2002) as it relies on actual and not predicted vulnerabilities. In addition, it zooms in on households that fall below a previous level of well-being and excludes those that are considered chronically MPI poor. Previous studies generally consider the chronically poor among those who are vulnerable (Calvo & Dercon, 2005). Third, the study addresses potential endogeneity problems due to simultaneity and self-selection in off-farm participation coming from observable and unobservable factors using a combination of propensity score matching (PSM) and the difference-in-difference (DID) estimation approach. Though this is not a new approach for studying well-being (Do et al., 2019), its use together with a comprehensive measure of poverty such as the MPI is an improvement and the regression coefficients have causal interpretations unlike previous studies that do not look at past correlations (Bezu & Barrett, 2012; Bezu et al., 2012). This study also looks at rural and small-town dwellers who are the largest group of poor in Ethiopia.

This study tries to understand multidimensional poverty and vulnerability in rural Ethiopia and the impact that off-farm participation has on these. In addressing this overarching objective, the study aims to:

- Measure the impact of participation in off-farm income generating activities on multidimensional poverty, and
- Measure the impact of participation in off-farm income generating activities on vulnerability to multidimensional poverty.

The rest of this paper is organized as follows. Section 2 discusses relevant literature on welfare and poverty and the impact of off-farm participation on poverty and vulnerability to poverty in developing countries. Section 3 discusses the data used and the methodology followed. Section 4 gives a systematic presentation of the results of the data analysis along with a discussion of the results. The final section gives a summary of the key findings of the study and makes some recommendations.

2. Review of off-farm participation, multidimensional poverty, and vulnerability

Off-farm activities in the rural parts of developing countries have certain salient features. There are limited employment opportunities for household members outside family farms and where the opportunities are available, they are often low paying unskilled wage employment or working in family run businesses. Better paying skilled jobs are usually available in faraway urban areas. Household members migrate to these urban areas to find employment (Mellor, 2017; Wiggins, 2014). In addition, the types of off-farm economic activities that households engage in depend on their level of wealth or well-being. Better-off households participate in off-farm activities if they are viable in terms of returns to investment while poor households participate in these activities in response to consumption distress (Djurfeldt & Djurfeldt, 2013; Woldehanna & Oskam, 2001). Rural dwellers often have limited access to credit, capital, and markets for their products. They have poor technological capacities and limited access to information. Rural areas also suffer from poor availability or complete absence of infrastructure and utilities because of the high costs of their provision (Ali & Peerlings, 2012).

The World Development Report (The World Bank, 2000; p. 15) defines poverty as "pronounced deprivation in well-being." It is not only a state of severe consumption deficit but also of other forms of deprivation such as "peace of mind" (Calvo, 2008). Existing studies have either used income-based measures of poverty or combined them with direct indicators of deprivation (Battiston et al., 2013). A definition of poverty close to that used in this study is a state of "clustering disadvantages," the clusters being the different dimensions of well-being such as food consumption, education, health, sanitation, and housing (Wolff &

De-Shalit, 2007, p.10). MPI operationalizes this definition as clustered disadvantages in health, education, and living standards.

MPI is by far the most popular and superior approach for measuring poverty in developing countries. It meets and exceeds the axiomatic properties of the Foster-Greer-Thorbecke class of poverty measures besides also addressing multiple deprivations directly (Alkire & Foster, 2011). Construction of the MPI has three parts. First, 10 welfare indicators categorized into three dimensions are chosen. Second, the deprived are distinguished from the non-deprived by defining an indicator specific threshold. Falling below this threshold is considered deprivation in the respective indicator. An additional cut-off is set on a weighted aggregation of these indicators. If a household scores above this cut-off, then it is considered MPI poor. The final part is determining the weights of the aggregation.

MPI is constructed with two principles in mind. First, it should reflect the poverty conditions in developing countries. Second, it should be easily comparable to other well-being measures such as the Human Development Index. Determining MPI's indicators, dimensions, and weights is largely driven by these two considerations (Alkire & Foster, 2011). It is for these reasons that this study uses MPI for measuring multidimensional poverty. However, as a departure from the equal weights approach used in Alkire and Foster's (2011) formulation and following Costa et al. (2018) this study uses the principal components analysis to generate the weights.

While poverty is failure to reach a poverty line, the threat of falling below this line is vulnerability to poverty. Vulnerability is the risk of falling into poverty in the future (Calvo & Dercon, 2005). It is measured as the risk of falling below the poverty line in the future given that a household is currently non-poor, or that a household will remain poor in the future given that it is currently poor. A less frequently used approach is focusing on those who are vulnerable to a fall in their welfare position.[32] In this approach, the actual loss of a welfare position over time is used for modeling vulnerability (Costa et al., 2018). Here, vulnerability is measured as the transitional probability of entering, remaining in, or getting out of a decile in the MPI distribution.

Conceiving vulnerability as a transitional probability gives the measurement of poverty better properties. First, it gives the exact state of vulnerability to poverty and the risk levels can be extracted ex-post. Second, it defines vulnerability irrespective of the current state of a household's poverty. Third, it can also show the intensity or depth of vulnerability in terms of the number of decile categories that a household jumps up or falls in the next period. Moreover, this approach does not rely on subjective risk perceptions, nor does it measure a household's welfare response to shocks; instead it directly looks at a household's movement up or down in poverty distribution.

Households diversify to spread the risks on their incomes. Off-farm participation is part of this diversification strategy. Off-farm participation may be in response to mitigating unforeseen deterioration in welfare or coping with actual welfare loss. The off-farm sector also functions as a residual employer providing employment to the underemployed rural labor and absorbing labor despite higher wages in farming (Bezu et al., 2012).

Several studies have shown that participation in off-farm activities contributes to household welfare in developing countries (Akaakohol & Aye, 2014; Bezu et al., 2012; Fox & Sohnesen, 2016; Ibrahim et al., 2017; Imai et al., 2015; Woldehanna & Oskam, 2000). However, very few studies establish a causal relationship running from off-farm participation to household

[32] These are classified as 'transient poor' in Chaudhuri et al. (2002) as opposed to the chronically poor.

welfare. Recent studies have addressed the issue of endogeneity. Zereyesus et al. (2017) used instrumental variables and feasible generalized least squares to control for endogeneity between off-farm participation and per capita consumption expenditure. Ibrahim et al. (2017) used propensity score matching to control for observable differences between participants and non-participants in off-farm income generating activities; however, they did not account for unobservable sources of the differences. Using data from Vietnam and India, Imai et al. (2015) found that off-farm participation had an impact on household poverty and vulnerability. These authors applied the treatment effects model to control for a self-selection bias in off-farm participation.

Unobserved factors, particularly characteristics that are specific to a study's subject and do not change over time, could drive both a household's decision to participate in off-farm activities and its state of poverty and vulnerability. Nguyen et al. (2015) combined propensity score matching with difference-in-difference to look at the impact of rural-urban migration on household welfare and vulnerability. Unlike their work, this study considers a broad array of off-farm activities.

3. Data and methodology

3.1. Data and variables

This study uses three waves (2011-12, 2013-14, and 2015-16) of the Ethiopian Socioeconomic Survey (ESS) panel data which is part of the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). The survey uses a two-stage probability sampling procedure. In the first stage, enumeration areas (EAs)[33] are sampled randomly proportional to the size of each of the four most populous regional states and a fifth block of the remaining smaller regional states. In the second stage, 15 households are selected from each EA randomly.

This study used ESS data on rural areas and small towns. ESS started with 3,969 households in rural and small towns in 2011-12. This number fell to 3,776 in 2013-14 and to 3,699 in 2015-16. Balancing the three rounds further reduced the sample size to 3,639 for each of the three rounds. Hence, the final sample used in this study is 10,917 households with 3,639 households in each wave.[34]

Data on household demographics, assets, shocks, and community level variables were extracted from the ESS data. For the construction of off-farm participation variables, all income generating activities other than farming and livestock rearing were considered as off-farm. Off-farm activities were categorized into three as high returns, low returns, and unearned. Family enterprises and permanent wage employment were classified as high return off-farm activities. Casual employment and employment in PSNP were recast as low return off-farm activities. Transfers were considered as unearned off-farm sources of income. For participation in each of these activities, an indicator variable was used which assumed a value of one if there was positive income from a source and zero otherwise.

[33] These are essentially villages. Small towns are towns with less than 10,000 inhabitants based on estimates from the 2007 Population and Housing Census.

[34] Attrition of households in subsequent panels may not be random. To correct for the possibility of this attrition bias the inverse of the predicted probabilities of a household being present in all three rounds was used as an additional explanatory variable.

The measurement of multidimensional poverty followed the Alkire and Foster (2011) methodology with a few changes in the measurement of indicators used in OPHI (2018) due to data unavailability. Table 4.1 gives a discussion of the definitions, measurements, and cut-offs for the indicators of MPI. Health deprivation does not include adult BMI-for-age data. Since data on child mortality was not available for the second wave, morbidity data was used instead. Poverty as measured by MPI is a key dependent variable in this study. Ten deprivation indicators are organized under health (nutrition and child mortality); education (years of schooling and school attendance); and living standards (cooking fuel, sanitation, drinking water, electricity, housing, and assets) dimensions. These deprivations are reduced to MPI using weights derived from a principal component analysis (PCA). The Kaiser normalization criterion was used for arriving at the principal components, and the principal components with eigenvalues greater than one were used for the construction of weights as in Costa et al. (2018) (See Appendix 4.1 for PCA results). MPI assumes values between zero (no deprivation) and one (deprived in all indicators).

Table 4.1. Multidimensional Poverty Index's dimensions and indicators' descriptions

Dimensions Indicator	Definition and measure	Weight		SDG
		Fixed	PCA	
Health				
Nutrition	Deprived if any child under 5 years old is underweight, stunted or wasted based on the WHO growth standards. (Child is undernourished, stunted or wasted if 2 SD below the median Z-score of the reference population). This indicator does not include adult household members' undernourishment because data is not available.	.167	.146	2
Child mortality	A household is deprived if it had a child under 5-years old who had died in the past 12 months. For round 1 of the survey, under 5 morbidity for the past 3 months of the survey was used to proxy mortality.	.167	.171	3
Education				
Years of schooling	A household is deprived if no member 10 years or older has at least six years of schooling. For child members' less than 20 years a maximum of 1 year of repetition was allowed assuming they start school at 8 years of age.	.167	.024	4
School attendance	A household is deprived if any school aged child is not attending school up to Grade 8.	.167	.149	4
Cooking fuel	Deprived if the household uses solid fuels: firewood, charcoal, crop residue, dung, manure, and saw dust.	.167	.048	7
Living Standard				
Sanitation	Deprived if the household's sanitation facility is not improved as per the MDG guidelines, or it is improved but shared with other households. Not improved sanitation facilities are defined as no toilet, or using bush toilet, field/forest.	.056	.062	11
Drinking water	Deprived if the household does not have access to safe drinking water according to MDG guidelines. Safe drinking water sources are tap private or shared, and protected well/spring and if water from unsafe sources is boiled.	.056	.014	6
Electricity	Deprived if household does not have access to electricity. A household has electricity if, at least its source of light, in addition to cooking, is electricity. Electric sources are electric meter, generator, solar, electrical battery, dry cell with switch; non-electric sources are kerosene light lamp (imported), kerosene lamp (*kuraz*), candle/wax, or firewood.	.056	.139	7

Housing	This indicator is a composite of three housing condition indicators - floor, wall, and roof. A household is deprived if low quality material is used in the construction of the floor, wall, or roof. Low quality floor materials are dirt, sand, or dung. Low quality wall materials are rudimentary materials which include wood and thatch, stone only, mud bricks (traditional), and reed/bamboo. Low quality roof materials are thatch, wood and mud, reed/bamboo, and plastic canvas.	.056	.117	11
Assets	Deprived in assets if the household does not own more than one of: a radio, TV, telephone, bike, motorbike, refrigerator, computer, or animal cart and does not own a car or truck.	.056	.130	1

Note: All indicators are measured as dummies where 1 indicates deprivation. Indicator cut-offs are constructed into the definitions of the indicators.

Source: author's definitions based on ESS data availability and Alkire and Foster (2011)

Another important dependent variable used in this study is vulnerability to MPI poverty.[35] Households were ranked in MPI deciles using MPI data from the first wave (2011-12). If a household transitioned to a higher MPI decile in the next period, it was identified as vulnerable to multidimensional poverty and not vulnerable otherwise. This study identified those households which remained in the same MPI decile in the subsequent waves as not MPI vulnerable. This makes for easier comparability between being MPI poor and being MPI vulnerable. The rest of the variables used as controls in this study are in Table 4.2. Summary statistics of these variables are given in Appendix 4.2.

Table 4.2. Definition and measurement of control variables

Category	Variable	Definition and measurement
Household Head characteristics	Sex	0 = M and 1= F
	Age	Age, its square in years
	Literate	1 = read and write
	School years	Highest years of schooling
Household wide characteristics	Age	Mean age of members, its square in years
	Dependency	Percent share of dependents in a household
	School years	Mean of highest years of schooling, all members, females
Household assets	Asset index	First principal component of PCA on 34 asset items
	Housing index	First principal component of PCA on 12 housing characteristics
	TLU	Livestock in tropical livestock units (Storck et al., 1991)
	Land size	Land owned in hectares
Shocks	Idiosyncratic	Death of household member, death of livestock
(1 if shock is present)	Correlated	Drought, flood, local unrest, food price increase, and input price increase which households ranked as one of three most severe shocks in the last 12 months
Community	Access and location	Distance from the nearest major road, local market in km; Households located in a woreda town

[35] MPI vulnerability led to the construction of a stochastic vulnerability index even though it is based on a deterministic dichotomous classification of a household's vulnerability status with axiomatic index properties that it borrows from its parent index, the multidimensional poverty index.

	Availability Dummies	One for the respective dummy variable if local market, health post,[36] hospital, commercial bank, MFI, and water services are available in the community
	Elevation	In meters

Source: author's construction of variables using ESS data

3.2. Conceptual framework of multidimensional poverty and vulnerability

The conceptual underpinning for studying the relationship between off-farm participation and multidimensional poverty and vulnerability is borrowed from Feeny and McDonald (2016). A household's multidimensional deprivation, d_{it}, can be given as:

(4.1) $$d_{it} = f\left(X_{it}, S_{it}, R_{it}, e_{it}\right)$$

An increase in d_{it} means a household has become more destitute with respect to one or more dimensions of well-being. X_{it} is a vector of demographic characteristics, socioeconomic status, livelihood sources, and asset endowments; S_{it} represents a vector of idiosyncratic and covariate shocks; and vector R_{it} represents household i 's response to negative shocks between $t-1$ and t in the form of off-farm participation.

This study approaches d_{it} as MPI poverty and MPI vulnerability. For MPI poverty, d_{it} is an indicator variable that assumes a value of one if a household's MPI is above 0.33 and zero if it is equal to or less than 0.33:

(4.2) $$d_{it} = \begin{cases} 1 & if\ MPI_{it} > 0.33 \\ 0 & if\ MPI_{it} \leq 0.33 \end{cases}$$

The probability of falling below MPI's 0.33 threshold can be modeled using probit or logit regressions.

MPI vulnerability is measured as the risk of falling into poverty in the next period. This risk is not observable but what can be observed is the mobility of households up or down the MPI distribution. In the context of this study, a household is vulnerable to multidimensional poverty if it moves up to a higher decile in the MPI distribution in the future relative to its current position. Let V be a variable measuring MPI vulnerability, then:

(4.3) $$V_{i,t+1} = \begin{cases} 1 & if\ D_{i,t} < D_{i,t+1} \\ 0 & if\ D_{i,t} \geq D_{i,t+1} \end{cases}$$

where $D_{i,t}$ is the MPI decile to which household i belongs at time t and $D_{i,t+1}$ is the MPI decile of i in the next wave, $t+1$. This vulnerability can be modeled as a latent variable, $V^*_{i,t+1}$,

which is a function of the explanatory variables and an error term:

(4.4) $$V^*_{i,t+1} = f\left(X_{i,t+1}, S_{i,t+1}, R_{i,t+1}, \varepsilon_{i,t+1}\right)$$

[36] A health post is part of the three-tier health system in Ethiopia that covers 3,000 to 5,000 individuals.

where $V^*_{i,t+1}$ is the probability of being vulnerable in the next wave. We cannot observe $V^*_{i,t+1}$. What we can observe though is the movement of households to a higher decile in the MPI distribution, $V_{i,t+1}$. Households move to a higher decile in the MPI distribution when $V^*_{i,t+1}$ is above a certain threshold, μ:

$$(4.5) \qquad V_{i,t+1} = \begin{cases} 1 & if\ V^*_{i,t+1} > \mu \\ 0 & if\ V^*_{i,t+1} \leq \mu \end{cases}$$

The risk of being vulnerable can then be modeled as a probit or logit regression where:

$$(4.6) \qquad P\left(V_{i,t+1} | \mathrm{X}_{i,t+1}, S_{i,t+1}, R_{i,t+1}\right) = \Phi\left(X_{i,t+1}\alpha + S_{i,t+1}\beta + R_{i,t+1}\delta + \varepsilon_{i,t+1}\right)$$

where $\Phi(.)$ can be a normal or logistic cumulative distribution function. Using this result, we can predict households' vulnerability to multidimensional poverty in the next period, $V_{i,t+1}$, using the coefficients obtained from a probit or logit regression in period t. Because the study uses three waves of data, vulnerability to multidimensional poverty in the future, $V_{i,t+1}$, was calculated for the last two survey waves in 2013-14 and 2015-16.

3.3. Empirical framework and causal identification

Identifying the impact of participating in off-farm income generating activities on household poverty can be complicated due to potential endogeneity coming from both observable and unobservable sources. Poor households may opt for off-farm activities when they experience a negative shock to their welfare. Studies also suggest that households at a low level of initial welfare opt out of off-farm activities when they experience improvements in their welfare levels (Bezu et al., 2012; Woldehanna & Oskam, 2001). These relationships are indicative of potential simultaneity between the decision to participate in off-farm activities and welfare. Another potential source of endogeneity is the systematic difference between those who decide to participate in off-farm activities and those who do not. For example, households with younger members tend to participate more in off-farm activities. More educated households also tend to be employed in high wage off-farm activities. Such behavior could lead to non-random sorting between participant and non-participant households. Whether the potential source of endogeneity is observable (such as a household's experience, level of education, access to markets, access to microfinance, and favorability for agricultural production) or unobservable (such as the propensity to take risks, entrepreneurial capital, and intellectual abilities), the relationship between off-farm participation and welfare must account for this to establish a causal relation.

Closely following Nguyen et al. (2015), this study focuses on addressing endogeneity that comes from observable and time invariant unobservable covariates. To purge endogeneity emanating from observable covariates, participant and non-participant households were matched based on their propensity to participate in off-farm activities (Rosenbaum & Rubin, 1983). For this decision, the propensity score, $e(x_i)$, for household $i, (i = 1, ..., N)$ is calculated as:

$$(4.7) \qquad e(x_{i,2011/12}) = \Pr(d_{\ i,2013/14|2014/15} = 1 | x_{i,2011/12}) \text{, and}$$

$$(4.8) \qquad \Pr(d_1, ..., d_n | x_1, ..., x_n) = \prod_{i=1}^{N} e(x_i)^{d_i} \{1 - e(x_i)\}^{1-d_i}$$

where $z_i = 1$ if any member of the household participates in an off-farm activity and $z_i = 0$ otherwise. x_i is a vector of observable covariates used in the matching process. The probit distribution is used for empirically calculating the propensity scores as in equation 4.8. The propensity score is between zero and one. A household that participates in an off-farm activity is matched with a corresponding non-participant household with a similar propensity score. This similarity can be decided using one of many approaches including nearest neighborhood (NN), caliper, and kernel matching. This study uses the NN and kernel matching approaches. Matching covariates are household head characteristics, household wide characteristics, assets, and community level characteristics. To ensure that the conditional independence assumption (CIA) is met, data from the first ESS wave (2011-12) was used for generating the propensity scores for participation in the subsequent two waves (2013-14 and 2015-16). This ensured that participation decisions did not in any way influence the covariates.

To purge endogeneity due to time invariant unobservables, this paper uses the DID estimator on the matched data. Accordingly, the average treatment effect (ATE) is calculated as:

$$\text{(4.9)} \quad \begin{aligned} ATE &= ATT - ATC \\ &= \{E(Y^T_{2015/16} - Y^T_{2013/14} \mid T = 1, P(X)) - E(Y^C_{2015/16} - Y^C_{2013/14} \mid D = 1, P(X))\} \\ &- \{E(Y^T_{2015/16} - Y^T_{2013/14} \mid T = 0, P(X)) - E(Y^C_{2015/16} - Y^C_{2013/14} \mid D = 0, P(X))\} \end{aligned}$$

The effect of off-farm participation on MPI poor or MPI vulnerable can be modeled as:

$$\text{(4.10)} \quad MPI_i = \alpha + \beta T_i + \gamma t_i + \delta (T_i * t_i) + \varepsilon_i$$

where ε_i is a random unobserved error. α is a constant term and gives the outcome level among non-participant households in 2013-14. β is a treatment specific effect which can be interpreted as the average treatment effect on the treated (ATET) in 2013-14 which is the effect of participation among participant households. γ is a time trend common to participant and non-participant households. δ is the true participation effect also known as the average treatment effect (ATE). Equation 4.10 is estimated using a two-way fixed effects regression controlling for both time and household fixed effects and exogenous shocks to household consumption and income. The coefficient on the treatment variable of this regression is equivalent to the true treatment effect estimate. In this technique, the time invariant unobservable covariates are differenced out and household fixed effects and other time invariant sources of endogeneity are removed. It is hoped that matching participants and non-participants will improve the parallel trends requirement for the DID estimator.

4. Results and discussion

4.1. Multidimensional poverty and vulnerability in rural Ethiopia

ESS data shows that multidimensional poverty has declined in rural Ethiopia. This decline is true both in terms of overall multidimensional poverty and specific deprivation indicators. Table 4.3 gives the deprivation scores for each of the 10 indicators, the overall MPI score, and the headcount ratio of MPI deprived households at the 33 percent cut-off level. These results are reported for each wave of ESS.

Under the health dimension, child mortality declined from 8 to 7 per 1,000 households.[37] Under the same dimension, child malnutrition (at least one case of a stunted or underweight child in a household) fell from 26.2 percent to 24.3 percent in ESS' three waves.

A look at the education dimension shows that there was a slight decline in the school attendance indicator while schooling improved. The school attendance indicator measured a deprivation if at least one school aged child in the household was not attending school. This is the only indicator that exhibited a deterioration during the study period. The share of households reporting such deprivation increased from 7.8 percent in 2011-12 to 8.9 percent in 2013-14 and fell to 7.9 percent in 2015-16. This means that households reporting at least one school aged child as not attending school increased by 0.1 percentage points. The schooling variable indicated that the number of households that did not have at least one member with 6 years of education or more dropped from 60.5 percent to 54.7 percent.

The living standards dimension has six indicators. The electricity indicator identifies households as deprived if their source of light is not electricity.[38] This level of deprivation fell from 65.0 percent to 29.6 percent between 2011-12 and 2015-16 showing remarkable progress in rural electrification. The safe drinking water indicator identifies a household as deprived if it fails to access drinking water from a safe source as per the millennium development goals' (MDGs) guidelines.[39] The share of rural households that did not have access to safe drinking water declined from 42.1 percent at the start of the survey to 30.7 percent at the end. Hence, substantial progress (a reduction of 11.4 percentage points) was made in terms of improving access to safe drinking water. The results also show that there was remarkable progress in sanitary conditions. The improved sanitation indicator measured deprivation if a household did not have access to a sanitary toilet.[40] The share of households that lacked improved sanitation fell by 32.4 percentage points or from 98.5 percent to 66.1 percent between 2011-12 and 2015-16. However, rural households that lacked improved housing[41] fell by a meagre 2.8 percentage points from 95.9 percent to 93.1 percent.

Households that lacked safe cooking fuel also fell by just 1 percentage point from 98 percent to 97 percent. The better asset conditions indicator showed a fall in the share of households that were deprived from 79.1 percent in 2011-12 to 76.2 percent in 2015-16 (a fall of 2.9 percentage points). All six indicators under the living standards dimension showed that the level of deprivation remained high in rural Ethiopia showing that there was large room for improvements. However, remarkable progress was made in rural electrification, sanitation, and safe drinking water provisions.

The MPI score for rural Ethiopia fell from 56 percent to 51 percent for the survey period. In other words, on average, rural households were deprived in 56 percent of the indicators in 2011-12. This figure fell by 5 percentage points in 2015-16. Based on the 0.33 cut-off on the MPI score, 89.4 percent of the rural households were deprived in 2011-12. This share fell by

[37] The figures for wave 2 (2013-14) wrongly suggest that under-5 mortality increased dramatically. This increase is because it uses child morbidity (child is sick at least for 3 months in the past 12 months) instead of mortality.

[38] Electrical sources include electricity meter, generator, solar, electric battery, or dry cell with a switch; sources that indicate deprivation are kerosene lamps, wax candles, or other non-electric sources.

[39] A drinking water source is safe if it is a tap inside the house, a private tap in a compound, a shared tap in the compound, a communal tap outside the compound, water from a kiosk/retailer, protected private well/spring, or shared protected spring/well.

[40] As per the MDGs' guidelines a sanitary toilet is one which is a private flushed toilet or a private ventilated pit latrine.

[41] A house is seen as having improved if its roof, floor, or walls use high quality material.

2.2 percent in 2013 and further by 2.5 percent in 2016. This means that households that were deprived in at least three of the 10 indicators fell by 4.7 percentage points in the survey period. This figure is modest compared to the 14 percentage points drop in the $1.90 based poverty headcount ratio for the same period in Ethiopia (Stifel & Woldehanna, 2016; UNDP Ethiopia, 2018). Moreover, it is also higher than the countrywide MPI. The countrywide MPI score was 0.49 in 2016 (OPHI, 2018).

Table 4.3. Summary statistics of multidimensional poverty indicators, MPI[42]

		2011-12		2013-14		2015-16	
Dimension	Indicator	Mean	Obs.	Mean	Obs.	Mean	Obs.
Health	Child mortality	0.008	3,611	0.015	3,638	0.007	3,639
	Child nutrition	0.262	3,517	0.243	3,409	0.243	3,409
Education	School attendance	0.078	3,639	0.089	3,639	0.079	3,639
	Schooling	0.605	3,639	0.583	3,639	0.547	3,639
Living standard	Electricity	0.650	3,611	0.501	3,636	0.296	3,639
	Safe drinking water	0.421	3,612	0.394	3,635	0.307	3,638
	Improved sanitation	0.985	3,639	0.973	3,639	0.661	3,639
	Improved housing	0.959	3,612	0.947	3,638	0.931	3,639
	Safe cooking fuel	0.980	3,603	0.977	3,621	0.970	3,639
	Better asset conditions	0.791	3,639	0.763	3,639	0.762	3,639
	Headcount, MPI deprived	0.894	3,480	0.872	3,386	0.847	3,408
	MPI score	0.560	3,480	0.540	3,386	0.510	3,408

Source: Author's calculations using ESS data.

Rural households had heterogeneous welfare gains during the study period. Previous studies have also acknowledged the existence of impact heterogeneity among different off-farm activities (Djido & Shiferaw, 2018). The heterogeneity in this study is given in Table 4.4 which calculates the share of households that fell below the 33.3 percent cut-off on the MPI score and the average MPI score for three different categorizations – off-farm participation, residence, and regional state. The results show that there were welfare improvements in each category over time. Moreover, there was a marked difference in the average MPI scores between or among categories. Households that participated in off-farm income generating activities had a lower MPI score compared to households that did not. This means that households that participated in off-farm activities were on average better off. This difference was persistent across all the three waves of the survey. Moreover, the gap between participants and non-participants increased over time. For the headcount measure of multidimensional poverty, the gap increased by 37.1, 38.8, and 40.0 percentage points and for the MPI score it increased by 36.4, 36.5, and 36.9 percentage points respectively for the first, second, and third waves. These results are suggestive of the presence of incremental changes in the welfare of the rural poor as a result of participation in off-farm income generating activities.

Urbanization of rural dwellings is another reason for the differences in the share of the poor who were deprived in at least a third of the indicators, H, and in the average MPI score,

[42] For calculating the MPI score and its decomposition, the Stata routine developed by Pacifico and Poege (2017) is used.

$M0$. Previous studies show that secondary towns such as the ones included in this study had a poverty reducing impact (Ingelaere et al., 2018) and hence the possibility of a higher MPI in urban areas. Moreover, the gap in terms of multidimensional poverty headcount, H, increased persistently over the survey period from 37.2 to 38.3 to 39.4 percentage points respectively in the three waves. However, the gap in terms of the MPI score, $M0$, fell from 28.8 to 27.3 to 25.1 percentage points respectively in the three waves. In terms of regional classifications, Tigray regional state was the most deprived (H=.906, $M0$=.959).

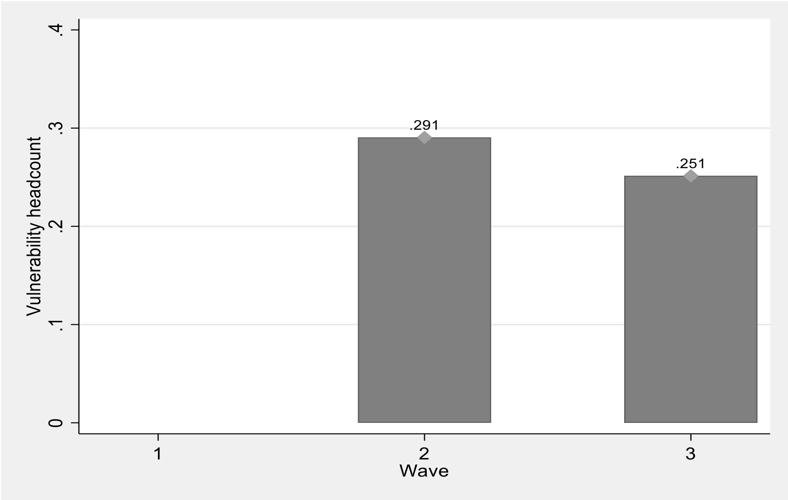
Table 4.4. A comparison of MPI for selected groups by survey waves

Group	Categories	Waves					
		MPI Headcount (*H*)			MPI (*M0*)		
		2011-12	2013-14	2015-16	2011-12	2013-14	2015-16
Off-farm income generating activities[43]							
	Non-participant	0.955	0.938	0.901	0.895	0.866	0.832
	Participant	0.584	0.550	0.501	0.531	0.501	0.463
Residence							
	Rural	0.940	0.924	0.894	0.585	0.554	0.490
	Small town	0.568	0.541	0.500	0.297	0.281	0.239
Regional state							
	Tigray	0.906	0.853	0.845	0.959	0.942	0.901
	Amhara	0.899	0.883	0.844	0.915	0.881	0.851
	Oromia	0.899	0.880	0.840	0.528	0.477	0.460
	SNNPRS	0.574	0.547	0.503	0.537	0.508	0.463
	Others	0.563	0.530	0.487	0.533	0.514	0.464

Note: The shares are calculated for a sample of 3,480 households in each wave.
Source: Author's calculations using ESS data.

The results given in Figure 4.1 show that there was a decline in vulnerability to multidimensional poverty during the survey period. The share of vulnerable households fell by 4 percentage points between 2013-14 and 2015-16. This small improvement suggests that the pace of reduction in multidimensional vulnerability was not as fast as the reduction in multidimensional poverty. This indicates that vulnerability to poverty is more difficult to address than current poverty.

[43] This refers to participation in at least any one of the three off-farm income generating activities.

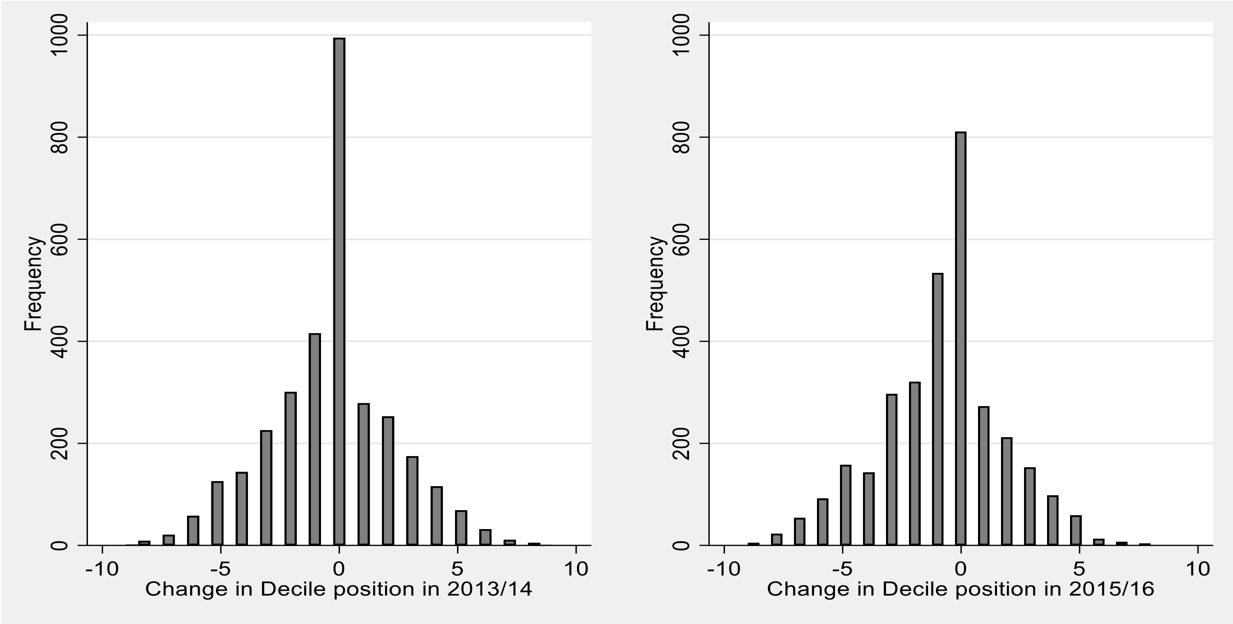


Source: Author's calculations using ESS data.

Figure 4.1. Multidimensional vulnerability headcount for the 2013-14 and 2015-16 waves

Figure 4.2 takes a closer look at vulnerability to multidimensional poverty. It shows whether households transitioned to a higher or lower MPI decile or remained in the same decile relative to 2011-12, an idea borrowed from the poverty transition matrix in Nguyen et al. (2015). Figure 4.2 shows that fewer households remained in their MPI decile in subsequent waves relative to 2011-12 even though the share of those who remained in their MPI deciles was the largest block among the sampled households. A closer look at the shape of the histogram shows that the length of the tallest block in the histogram, representing those who retained their MPI decile position, is shorter in 2015-16 relative to 2013-14. Hence, fewer households remained in their decile positions in 2015-16 relative to 2013-14. Moreover, the bars to the left of this tallest bar are taller in 2015-16 relative to 2013-14. This means more households dropped to lower deciles in 2015-16 than in 2013-14, which further means that more households became less vulnerable in 2015-16 than they were in 2013-14. On the other hand, inspecting the bars to the right of the tallest bar for both panels in Figure 4.2 shows that there were many households that transitioned to a higher MPI decile in both 2013-14 and 2015-16 relative to 2011-12. This suggests that a considerable number of households became vulnerable to multidimensional poverty in 2013-14 and 2015-16.

Figure 4.2 also shows that the higher the number of deciles transitioned, the fewer the households that transitioned. This serves as a visual of the severity of vulnerability. A thinner right tail in 2015-16 means that vulnerability to poverty was less severe in 2015-16 than it was in 2013-14. Overall, there was a great deal of mobility of households to both higher and lower MPI deciles.



Source: Author's calculations using ESS data.

Figure 4.2. MPI decile transitions in 2013-14 and 2015-16

The relationship between multidimensional poverty and vulnerability is such that almost all households that are not MPI vulnerable are MPI poor. Put differently, a household is MPI vulnerable if it is MPI poor and not the other way around. Hence, MPI vulnerability acts as an added qualifier of a household's multidimensional poverty situation in addition to MPI poverty (refer to Appendix 4.3 and Appendix 4.4).

Table 4.5 expands on the results that households that participated in off-farm activities had lower multidimensional poverty (see Table 4.4). It gives the prevalence of MPI deprived and MPI vulnerable households in the sample by their participation in one of the three categories of off-farm activities. Among those who participated in high return off-farm activities, 81 percent were MPI deprived while 26 percent were MPI vulnerable. Among the participants in low return off-farm activities, 91.4 percent were MPI deprived while 26.2 percent were MPI vulnerable. Among households receiving incomes from unearned off-farm sources, 84.7 percent were MPI deprived and 27.5 percent were MPI vulnerable. Households that participated in low return off-farm activities were both more MPI deprived and more MPI vulnerable than households that participated in high return off-farm activities.

Table 4.5. Prevalence of MPI poverty and MPI vulnerability by off-farm participation

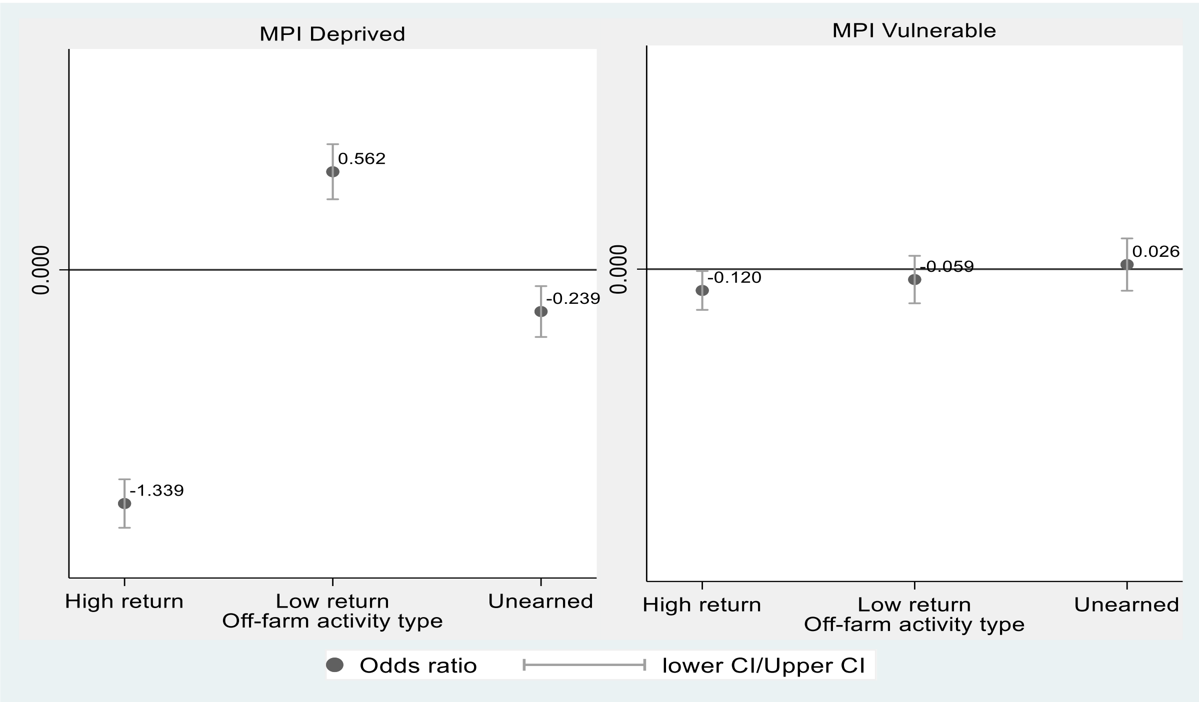
Off-farm participation type	MPI Deprived		MPI vulnerable	
	Share	Number	Share	Number
High return activities	0.810	5,523	0.260	3,460
Low return activities	0.914	2,333	0.262	1,405
Unearned activities	0.847	1,733	0.275	1,061

Note: N=10,274 for MPI deprived; N=6,496 for MPI vulnerable.

Source: Author's calculations using ESS data.

Continuing with the study of welfare differences between participants and non-participants in off-farm activities, this study focuses on the multidimensionally poor and vulnerable to understand which of the three off-farm categories were associated with being MPI deprived and which ones were associated with being MPI vulnerable. Figure 4.3 presents the differences in the odds ratios. The panel to the left plots the odds ratio of being MPI deprived to not being MPI deprived for each of the three categories of off-farm participation. The odds of being MPI deprived for those who participated in high return off-farm activities were 1.339 times less than the odds for those who did not participate in off-farm income generating activities. In a similar manner, the odds of being MPI deprived for participation in unearned sources of off-farm income were 0.239 times less for households that did not participate. For participation in low-return activities, the association between being MPI deprived and off-farm participation flipped in the opposite direction. The odds of being MPI deprived were 0.56 times more for those who participated relative to the odds of those who did not.

The association between MPI vulnerability and the three categories of off-farm participation was dampened relative to that observed for MPI. There was no statistically discernible association between being MPI vulnerable and off-farm participation in low return off-farm activities and unearned off-farm activities. However, the odds of being MPI vulnerable were 0.12 times less for households that participated in high return off-farm income generating activities relative to those who did not participate.



Note: The odds ratios are calculated by way of a univariate logit regression.
Source: Based on the author’s calculations using ESS data.

Figure 4.3. Association between being MPI deprived and MPI vulnerable vis-à-vis off-farm participation

The findings so far show that households that participated in off-farm activities were less likely to be MPI poor. It also appears that this difference in welfare came from participation in high return off-farm activities and unearned off-farm sources. Of these, participation in high return activities seems to carry over to better welfare outcomes in terms of reduced MPI vulnerability. These results, however, imply a correlation or association but they do not necessarily imply a causal relation between the two.

4.2. Econometric analysis

4.2.1. Main results

To match participant and non-participant households in terms of observable characteristics, this study used the PSM method and Kernel weights. To ensure that CIA was met, households were matched using covariate data only from the 2011-12 wave on households' decisions to participate in the subsequent two waves. Households were balanced on household head's characteristics (age, age squared, literacy, and years of schooling); household wide characteristics (mean age, mean years of schooling, and dependency); household endowments (owned land, asset index, housing index, and livestock in TLU); and community characteristics (distance to the nearest major road, distance to the local market, availability of a health post, hospital, commercial bank, MFI, water service in the community, whether the community was in a woreda town, and elevation). A quick inspection of the balancing property of PSM shows that this property was met.[44] Figure 4.4 shows that this was the case for each of the three off-farm activity categories. For each of the three panels there is a considerable area of overlap (refer to Appendix 4.6 for the overlap). Therefore, participants and non-participants were balanced across observable characteristics.

Source: Based on author's calculations using ESS data.

Figure 4.4. Propensity score histograms by non-participants and participants

[44] A formal test of the balancing property also clearly shows that the balancing property is met for each of the three categories of income generating off-farm activities. The results are given in Appendix 4.5.

Once households were matched for observable covariates, unobservable sources of endogeneity were controlled for using the DID method. Since the first wave (2011-12) was used for balancing, the DID estimator was applied to the remaining two waves also (2013-14 and 2015-16). The results are reported in Table 4.6 where shocks, idiosyncratic and correlated, were used as controls because they are exogenous to MPI poverty and off-farm participation. The DID estimator was also calculated for the full sample for comparison and for the first and last tertiles of the MPI poverty index's distribution. The coefficient of the off-farm participation dummy variable is reported as the DID estimate along with its corresponding standard error. All regressions are controlled for year and household fixed effects.

Table 4.6. Difference-in-difference estimates by off-farm activities[45]

Type of off-farm activity	MPI Deprived		MPI Vulnerable	
	Kernel	Nearest Neighbor	Kernel	Nearest Neighbor
	(1)	(2)	(3)	(4)
High return	-0.122**	-0.475**	-0.050	-0.188
	(0.050)	(0.232)	(0.038)	(0.160)
N	608	652	1,154	1,158
Low return	-0.069	-0.246	-0.081	-0.365*
	(0.067)	(0.247)	(0.050)	(0.187)
N	608	652	1,154	1,148
Unearned	-0.037	-0.122	-0.020	-0.046
	(0.063)	(0.254)	(0.041)	(0.170)
N	608	650	1,154	1,146

Note: The DID regressions for MPI poverty and MPI vulnerability are done using Stata's conditional logit routine -*clogit*-.
All regressions are controlled for year fixed effects and household fixed effects.
Regressions reported in Columns 2, 4, 6, and 8 are controlled for shocks.[46]
*** p<0.01, ** p<0.05, * and p<0.1.
Source: Author's calculations using ESS data.

Columns 1 and 2 of Table 4.6 give DID estimates for being MPI deprived where Column 1 gives the results for the Kernel weighted data and Column 2 for the nearest neighbor matched data. The DID coefficient gives the impact of off-farm participation as an odds ratio. The results show that the impact of off-farm participation was statistically significant for the high return category with the Kernel estimate reporting a lower DID estimate. Relative to not

[45] Studies classify off-farm activities to reflect that income generating off-farm activities are quite diverse. There are different ways of recognizing this heterogeneity such as the RIGA criteria used by FAO (Covarrubias et al., 2009). This study adopts a classification similar to that used by Djido and Shiferaw (2018).
[46] The shocks included are both idiosyncratic household level shocks and correlated shocks. The household level shocks are the death of a household member and death of livestock. The correlated shocks include drought, flooding, local unrest, food price rises, and input price rises.

being MPI deprived, participation in high return off-farm activities reduced the odds of being MPI deprived by 0.122 times for the Kernel matched data and 0.475 times for the nearest neighbor matched data. The average treatment effect (ATE) of off-farm participation in low returns and unearned off-farm activities was not statistically significant. Even though previous studies do not distinguish between the categories of off-farm participation, they confirm that participation has a positive welfare effect (Ibrahim et al., 2017).

Columns 3 and 4 of Table 4.6 gives the DID estimates for being MPI vulnerable. The high return and unearned categories of off-farm participation did not return significant coefficients. Therefore, participation in off-farm income generating activities had no impact on rural households' vulnerability to multidimensional poverty. This finding is in contrast to a previous study that proxied vulnerability with a fall in future household consumption (Zereyesus et al., 2017). However, its findings are similar to Nguyen et al. (2015).

4.2.2. Heterogeneity in off-farm participation impact

To look at the impact heterogeneity of off-farm participation on rural multidimensional poverty and vulnerability, the first and last tertiles of the MPI distribution were taken. Again, participant and non-participant households were matched using Kernel weights and propensity scores based on the nearest neighbor method, followed by a DID estimation for measuring the causal effect of participation in off-farm activities on MPI deprivation and MPI vulnerability.

Table 4.7 gives the coefficients of the off-farm participation dummy of these estimations. The regressions controlled for idiosyncratic household and correlated shocks. The coefficient of the participation dummy can be interpreted as a measure of the impact of off-farm participation. This coefficient turns statistically significant only for the third tertile under the low return off-farm activities category for the nearest neighbor matched data. Participating in low return off-farm income generating activities reduces the odds of being MPI deprived by 1.534 relative to not being MPI deprived for households in the third tertile – households that are the poorest of the poor. Participating in low return off-farm income generating activities reduces the odds of being MPI vulnerable by 0.279 for the Kernel matched data. However, in both cases the results are not definitive because these results are not significant when the other matching technique is used. However, one conclusion that can be drawn is that there are tell-tale signs of impact heterogeneity, particularly among participants in the low return activities category and for the poorest of the poor. Participation in the high return or the unearned categories does not have any significant effect on being MPI deprived or MPI vulnerable.

Table 4.7. Difference-in-difference estimates for the first and third tertiles by off-farm activities

Type of off-farm activity	MPI Deprived				MPI Vulnerable			
	1st tertile		3rd tertile		1st tertile		3rd tertile	
	Kernel	NN	Kernel	NN	Kernel	NN	Kernel	NN
High return	-0.111*	-0.438	-0.002	-1.574	0.012	-0.226	0.097	-0.105
	(0.062)	(0.283)	(0.005)	(1.138)	(0.133)	(0.235)	(0.141)	(0.761)
N	428	440	1,707	66	158	618	96	142
Low return	-0.068	-0.276	0.003	-1.534**	0.030	-0.282	-0.279**	0.012
	(0.085)	(0.293)	(0.006)	(0.737)	(0.158)	(0.236)	(0.125)	(0.468)
N	428	440	1,707	66	158	614	96	140
Unearned	-0.041	-0.163	-0.007	-0.990	-0.051	-0.094	0.058	0.935
	(0.074)	(0.308)	(0.007)	(0.987)	(0.108)	(0.224)	(0.145)	(0.576)
N	428	440	1,707	66	158	612	96	142

Note: Regressions are controlled for household fixed effects, year fixed effects, and shocks.
The DID regressions for MPI poverty and MPI vulnerability were done using a conditional logit routine -*clogit*- on Stata 15; *** p<0.01, ** p<0.05, and * p<0.1.
Source: Author's calculations using ESS data.

5. Conclusion and policy implications

This study looked at household poverty as a multidimensional concept and also included vulnerability to multidimensional poverty. Within this multidimensional framework, it also studied the impact of participating in off-farm activities on poverty and vulnerability where off-farm activities were categorized into high return, low return, and unearned activities. It defined multidimensional poverty in terms of the multidimensional poverty index (MPI) and vulnerability to MPI poverty as mobility to a higher decile in the MPI distribution.

Profiling multidimensional poverty showed that about 89.4 percent of the rural households were multidimensionally deprived in 2011-12. Even though this figure fell to 84.7 percent in 2015-16, it was still very high. On average, a rural household in Ethiopia was deprived in 5.6 of the 10 indicators used for constructing the MPI. The deprivation was the largest for indicators in the living standards dimension.

Vulnerability to multidimensional poverty declined between 2011-13 and 2015-16 from 29.1 percent to 25.1 percent. A more detailed exploration of the vulnerability profile of rural households showed that most of these households remained in their 2011-12 MPI deciles. The modest reduction in vulnerability came from more households moving down to a lower decile than households moving to a higher decile. These profiles of rural multidimensional poverty and vulnerability imply that poverty reduction strategies are pointing in the right direction and are also forward looking. However, the share of multidimensionally deprived households is still very high as over a quarter of the households were vulnerable to multidimensional poverty. This signals that more efforts should be made for reducing deprivations among rural households and it should also be ensured that they do not face the risk of falling into more deprivation in the future. This study showed that MPI vulnerability is less of a problem for MPI poor and more of a problem for households who are not MPI poor.

For households that were deprived in at least a third of the MPI indicators, the study found that there was a statistically significant difference in the odds of being MPI deprived between participants and non-participants in off-farm activities. Participants in high return and unearned categories had lower odds while participants in low return activities had higher odds of being MPI deprived. There were no differences between participants and non-participants in the low return and unearned categories. The difference was statistically significant only for the high return category where households had statistically significant lesser odds of being MPI vulnerable.

The study combined matching methods and DID methods to address potential endogeneity. Only the impact of participation in the high return category on MPI deprivation survived a causal interpretation. Off-farm participation did not impact vulnerability to MPI poverty. In terms of MPI tertile heterogeneity, off-farm participation reduced the odds of being MPI deprived and MPI vulnerable for the last tertile in the low return category, indicating that participation in low return activities had a welfare improving effect for the poorest. However, this last result was not definitive.

Based on these key findings, this study makes the following recommendations. First, participation in off-farm income generating activities has a multidimensional poverty reducing effect only for the high return category. These activities are family run small businesses and permanent wage employment. Therefore, policies aimed at improving rural well-being should incentivize households to participate in family enterprises and permanent wage employment. Second, the multidimensional poverty reducing effect of off-farm participation varied among households depending on their location in the MPI distribution. As an interesting case, the study found that off-farm participation in the low return category led to improvements in the multidimensional poverty of the poorest MPI tertile. Therefore, the provision or creation of low paying jobs such as PSNP and casual labor should be directed towards the poorest rural households for it to have a material impact on poverty reduction. Finally, off-farm participation had no causal impacts on a household's vulnerability to multidimensional poverty. This result is consistent for all three off-farm activities categories. Therefore, policies designed to reduce future risks to multidimensional poverty should not rely on nudging households to participate in off-farm income generating activities.

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Appendix 4

Appendix 4.1. Key results of PCA for generating aggregation weights for MPI's calculation

Principal components/correlation	Number of obs	=	10,274
	Number of comp.	=	10
	Trace	=	10
Rotation: orthogonal varimax (Kaiser on)	Rho	=	1.0000

Component	Variance	Difference	Proportion	Cumulative
Comp1	1.64256	.385251	0.1643	0.1643
Comp2	1.25731	.158188	0.1257	0.2900
Comp3	1.09912	.0910214	0.1099	0.3999
Comp4	1.0081	.0471245	0.1008	0.5007
Comp5	.960976	.0406546	0.0961	0.5968
Comp6	.920322	.0626279	0.0920	0.6888
Comp7	.857694	.0165343	0.0858	0.7746
Comp8	.84116	.0757793	0.0841	0.8587
Comp9	.76538	.118007	0.0765	0.9353
Comp10	.647373	.	0.0647	1.0000

Appendix 4.2. Summary statistics of the variables used for studying the determinants of multidimensional poverty and vulnerability

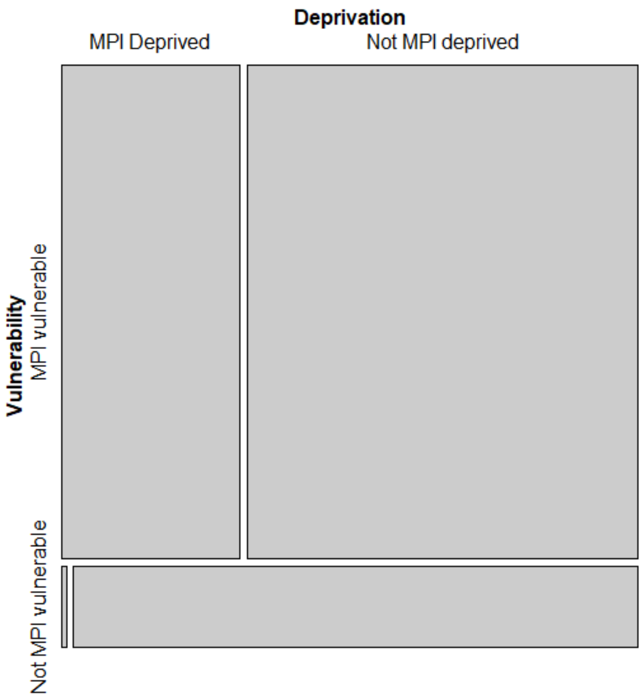
Category	variable	2011-12					2013-14					2015-16				
		Mean	St. dev.	Min	Max	N	Mean	St. dev.	Min	Max	N	Mean	St. dev.	Min	Max	N
Household head																
	Age	44.39	15.53	15	100	3594	45.92	15.26	0	99	3639	47.55	15.26	0	98	3639
	Age^2	2211.39	1552.52	225	10000	3594	2340.88	1549.73	0	9801	3639	2493.45	1591.48	0	9604	3639
	Sex	0.24	0.43	0	1	3594	0.25	0.43	0	1	3638	0.26	0.44	0	1	3638
	Schooling	2.06	3.52	0	16	3560	2.11	3.63	0	18	3599	2.24	3.78	0	17	3610
	Literate	0.40	0.49	0	1	3581	0.40	0.49	0	1	3608	0.42	0.49	0	1	3621
Household wide																
	Mean age	24.23	12.49	7	94	3639	23.58	11.61	6	91	3639	21.59	11.27	0	93	3639
	Dependency	46.44	24.73	0	100	3639	48.40	22.99	0	100	3639	55.50	21.68	0	100	3639
	Mean schooling	2.23	2.61	0	16	3639	2.42	2.66	0	17	3639	2.54	2.62	0	16	3639
Assets																
	Asset index	0.03	0.09	0	1	3639	0.09	0.07	0	1	3639	0.14	0.08	0	1	3639
	Housing index	0.13	0.10	0	1	3639	0.23	0.16	0	1	3639	0.21	0.13	0	1	3639
	TLU	2.33	3.62	0	87	3639	2.65	3.57	0	65	3639	3.48	9.77	0	538	3639
	Owned land	1.39	3.72	0	77	3639	1.34	4.54	0	126	3639	1.37	7.45	0	427	3639
Shock																
	Death of hh member	0.03		0	1	3639	0.02		0	1	3639	0.02		0	1	3639
	Death of livestock	0.00		0	1	3639	0.00		0	1	3639	0.00		0	1	3639
	Drought	0.15		0	1	3639	0.09		0	1	3639	0.30		0	1	3639
	Flood	0.03		0	1	3639	0.02		0	1	3639	0.01		0	1	3639
	Food price increase	0.24		0	1	3639	0.14		0	1	3639	0.20		0	1	3639
	Input price increase	0.11		0	1	3639	0.07		0	1	3639	0.13		0	1	3639
	Local unrest	0.00		0	1	3639	0.00		0	1	3639	0.02		0	1	3639
Off-farm activities																
	Overall	0.64		0	1	3639	0.62		0	1	3639	0.64		0	1	3639
	High returns	0.54		0	1	3639	0.53		0	1	3639	0.53		0	1	3639
	Low returns	0.25		0	1	3639	0.20		0	1	3639	0.23		0	1	3639

Unearned	0.18		0	1	3639	0.16		0	1	3639	0.16		0	1	3639
Community wide															
Commercial bank	0.95		1	2	3639	1.92		1	2	3639	1.90		1	2	3627
Health post	0.14		1	2	3639	1.11		1	2	3456	1.09		1	2	3481
Hospital	0.72		1	2	3639	1.69		1	2	3606	1.68		1	2	3629
MFI	0.72		1	2	3639	1.72		1	2	3639	1.72		1	2	3627
Water service	0.74		1	2	3639	1.69		1	2	3639	1.68		1	2	3627
Nearest Major Road	16.38	21.53	0	242	3608	16.34	21.40	0	242	3639	16.19	21.49	0	271	3639
Nearest Market	67.37	49.94	1	283	3608	67.52	50.35	0	283	3639	67.41	50.49	1	283	3639
Elevation (m)	1849.75	586.58	201	3311	3608	1846.94	586.60	201	3451	3639	1847.74	583.50	203	3357	3639
Small town	0.11		0	1	3639	0.11		0	1	3639	0.11		0	1	3639

Appendix 4.3. Contingency table of MPI deprivation and MPI vulnerability

		MPI vulnerable								
		Pooled			Wave 2			Wave 3		
		No	Yes	Total	No	Yes	Total	No	Yes	Total
MPI	No	904	7	911	413	4	417	491	3	494
Deprived	Yes	3,832	1,753	5,585	1,885	937	2,822	1,947	816	2,763
	Total	4,736	1,760	6,496	2,298	941	3,239	2,438	819	3,257

Appendix 4.4. Overlap between MPI deprived and MPI vulnerable households



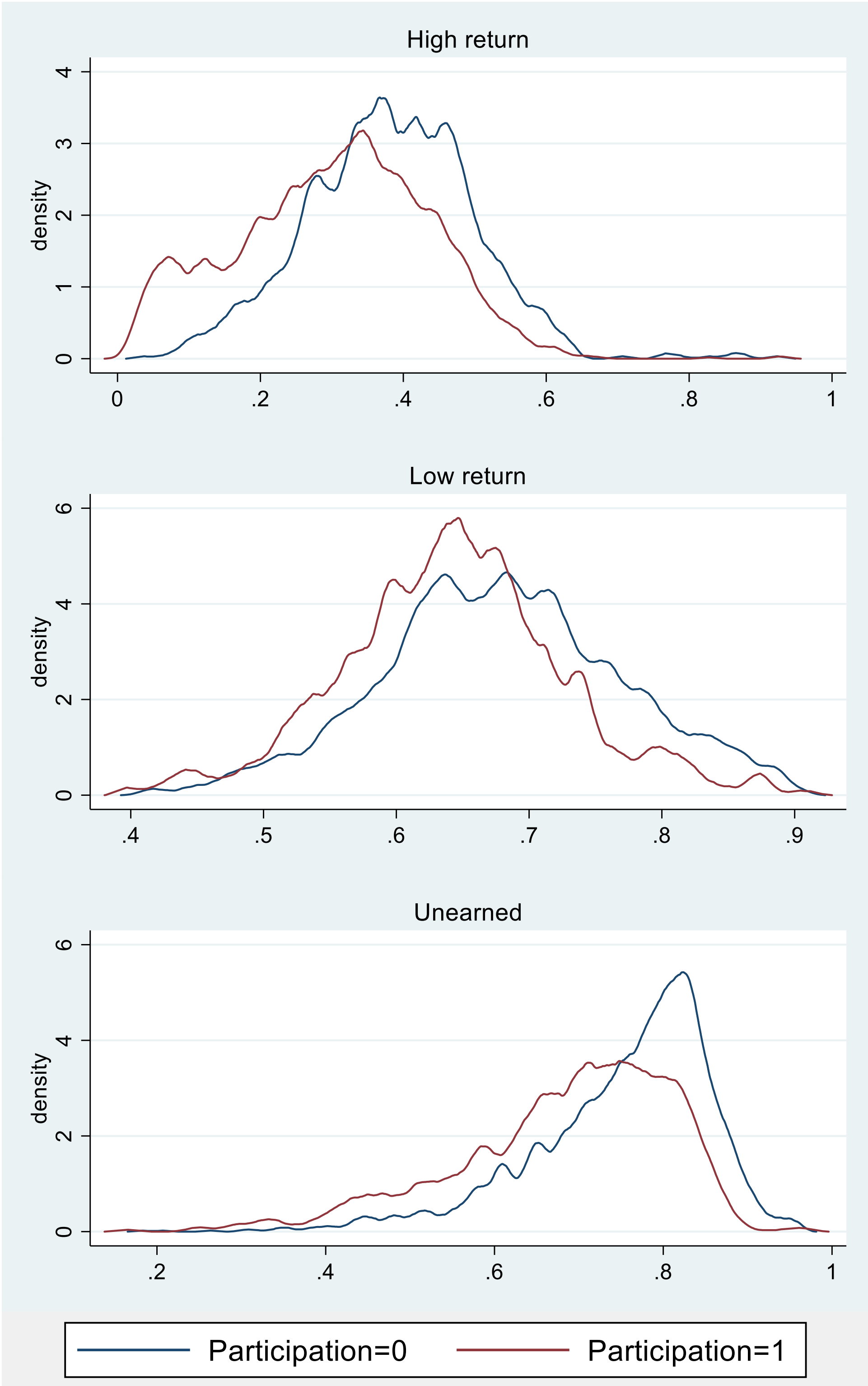
Source: Based on author's calculations using ESS data.

A household that is both MPI vulnerable and MPI poor is worse-off than a household that is only MPI poor. Generally speaking, a household that is not MPI vulnerable is also not MPI deprived. Hence, the level of well-being in increasing rank order will be (1) MPI deprived and MPI vulnerable, (2) MPI deprived but not MPI vulnerable, (3) Not MPI deprived but MPI vulnerable, and (4) Both not MPI deprived and MPI vulnerable. This empirical property makes it a good measure in that it serves as an added feature for a study of households' welfare.

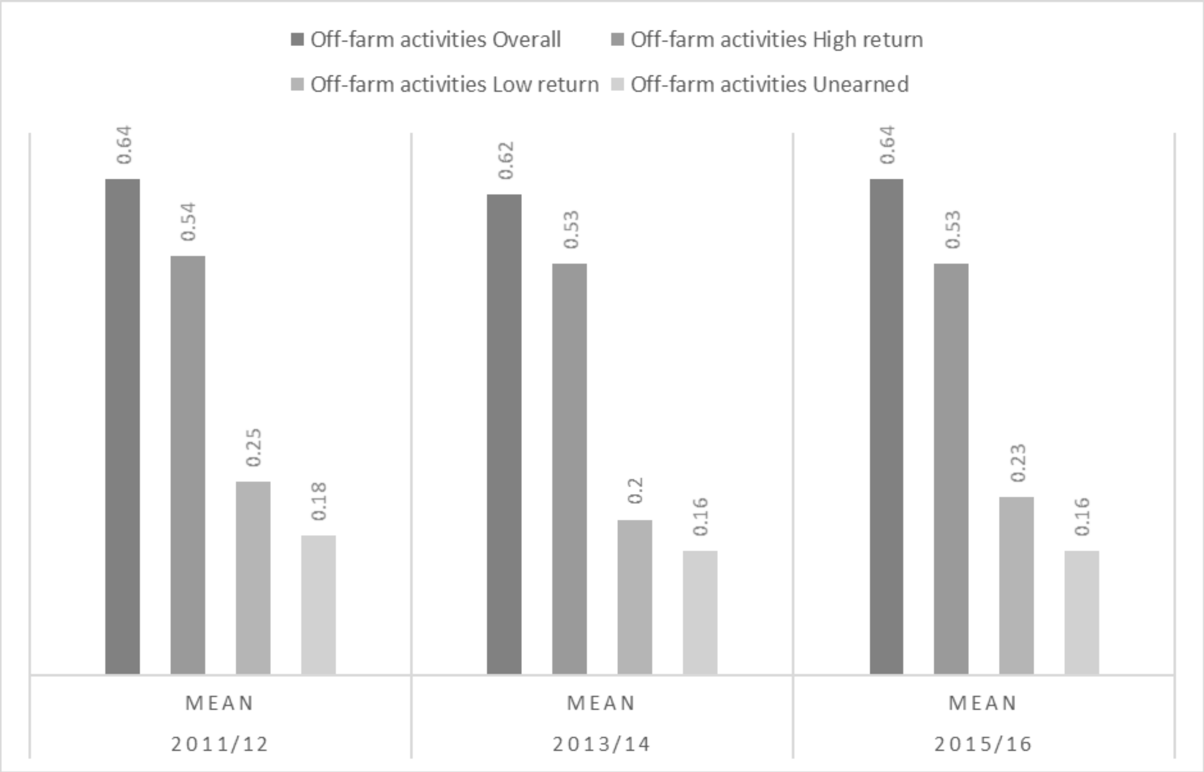
Appendix 4.5. Formal test of balance before and after matching

Covariates	High return				Low return				Unearned			
	Standardized differences		Variance ratio		Standardized differences		Variance ratio		Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
Agehd	0.03	0.03	1.16	0.98	-0.15	0.04	0.80	1.07	0.32	0.01	1.36	1.01
Agehdsqrd	0.05	0.03	1.23	1.01	-0.17	0.04	0.75	1.11	0.33	0.01	1.55	1.01
agehh_m	0.15	0.02	1.22	1.10	-0.20	0.00	0.66	1.06	0.34	0.02	1.73	1.04
schyr_mn	0.44	0.04	3.20	1.42	-0.15	-0.05	0.54	0.65	0.09	0.03	1.34	1.05
plt_own	-0.19	-0.05	0.36	0.94	-0.04	0.05	1.83	2.87	-0.25	0.06	0.59	1.35
Asti	0.18	-0.03	2.16	0.57	-0.08	0.05	1.00	2.53	0.13	0.05	3.35	1.81
Srtm	-0.09	0.07	1.21	1.09	-0.18	-0.03	0.99	0.90	-0.06	0.06	1.16	1.08
dist_road	0.02	-0.04	1.35	0.93	-0.06	0.02	0.56	1.09	0.03	0.00	0.76	0.79
dist_market	-0.12	-0.01	0.82	0.91	-0.14	0.02	0.78	0.89	-0.12	0.02	0.78	0.89
Rdwrthd	0.18	0.01	1.08	1.00	-0.03	-0.04	0.99	0.98	-0.10	-0.01	0.96	1.00
Sexhd	0.20	0.00	1.31	1.00	-0.06	0.02	0.93	1.02	0.29	0.00	1.35	1.00
alt_dpratio	-0.11	0.04	1.20	0.93	-0.02	0.03	0.85	0.92	0.04	0.01	1.31	0.99
wrdtwn_D	-0.29	0.05	2.39	0.88	0.08	0.02	0.82	0.96	-0.10	0.02	1.28	0.94
mkt_D	-0.11	-0.02	1.01	1.00	0.09	-0.01	0.99	1.00	0.01	0.01	1.00	1.00
hlthp_D	0.10	-0.11	1.25	0.81	0.11	0.04	1.26	1.08	0.09	-0.05	1.20	0.90
hosp_D	-0.20	-0.01	1.24	1.01	-0.01	0.01	1.01	0.99	-0.16	-0.01	1.15	1.01
cmmb_D	-0.23	0.00	3.04	0.99	0.04	0.01	0.85	0.98	0.00	0.05	1.02	0.80
mfi_D	-0.15	0.02	1.18	0.98	0.10	-0.01	0.90	1.01	-0.02	-0.01	1.02	1.01
wtr_D	-0.27	-0.02	1.39	1.02	0.07	0.01	0.93	0.99	-0.12	-0.01	1.14	1.01
Total obs.	3,441	6,882			3,410	6,820			3,421	6,842		
Treated obs.	2,317	3,441			1,135	3,410			912	3,421		
Control obs.	1,124	3,441			2,275	3,410			2,509	3,421		

Appendix 4.6. Overlap between participants before and after matching for main results



Appendix 4.7. Households that engaged in off-farm activities



Appendix 4.8. Contribution of each indicator and dimension to the MPI score

Dimensions	Indicator	MPI contribution by waves (percent)		
		2011-12	2013-14	2015-16
Health		9.05	8.33	8.76
	Child mortality	0.27	0.44	0.14
	Child malnutrition	8.78	7.89	8.62
Education		16.66	17.15	17.39
	School attendance	0.41	0.44	0.41
	Schooling	16.25	16.71	16.98
Living Standard		74.29	74.52	73.85
	Electricity	6.08	5.05	3.08
	Safe drinking water	5.11	4.47	3.80
	Improved sanitation	2.60	2.66	1.87
	Improved housing	22.82	23.53	24.45
	Safe cooking fuel	18.70	19.58	20.38
	Asset conditions	18.98	19.22	20.28

Note: The shares are calculated for a sample of 3,639 households in each wave.
Source: Author's calculations using ESS data.

Chapter Five: Agricultural Commercialization and Off-farm Incomes in Rural Ethiopia

(Paper 4)

Abstract

This paper explores the role of income generating off-farm activities in agricultural commercialization in rural Ethiopia. Agricultural commercialization is proxied by crop sales. The study measures the effect of a household's decision to participate in off-farm income generating activities and the effect of this income or crop sales. It uses a Heckman selection model modified to allow for the panel structure of the Ethiopian Socioeconomic Survey data to account for the non-randomness of a household's decision to engage in crop sales. The results show that off-farm participation affects the decision to engage in crop sales positively. Off-farm incomes, however, are found to discourage participation in crop sales. Neither, however, has an effect on crop sales. A key takeaway of this result is that even though off-farm participation and income can influence households' likelihood of commercializing, they do not guarantee an effect on the incomes from such commercialization. Additional incentives such as provision of extension services will help the likelihood of engaging in crop sales for improving incomes from crop sales.

Keywords: agricultural commercialization; off-farm income; Heckman sample selection model

JEL classification codes: D13; O13; Q12

1. Introduction

1.1. Background

Agriculture remains the dominant source of livelihood in sub-Saharan African (SSA) countries in general and in Ethiopia in particular. While own agricultural production remains the main source of household consumption, it also serves as an important source of income to meet households' non-food consumption needs. Rural households may sell their surplus agricultural produce and use this income for financing family members' expenditure on health, education, clothing, sanitation, and other non-food items. In rural Africa, it is also quite common for households to sell crops in the market even in the absence of a production surplus. This is usually done in times of consumption shocks (Campbell, 1990). Other households produce cash crops exclusively and use the proceeds to meet their food and non-food expenditure requirements (Barrett et al., 2005).

Agricultural commercialization is not necessarily about large scale commercial agriculture; it can also be about targeting the generation of surplus production among smallholders or the act of engaging in crop sales by poor rural households to cope with consumption shocks. Even though the advantage of economies of scale come with large scale agricultural commercialization, small scale commercialization has its advantages too. First, there is a sizeable portion of rural households engaged in agriculture in low-income countries. Second, small commercial farmers create significant demand for non-farm products among the rural poor since they spend about half of their incremental incomes in local rural economies. Third, small commercial farmers have larger labor productivity increases relative to large commercial farmers in response to yield increasing technological changes. With institutional support mechanisms such as availability of yield increasing technologies, the returns for small commercial farmers are higher than those from large scale farms (Mellor, 2017). Therefore, if one wants to address rural poverty in SSA and in Ethiopia, smallholder agricultural commercialization is among the places to start.

On the other hand, income from off-farm sources can also be used for purchasing additional inputs for crop production like fertilizers, irrigation pumps, semi-mechanized tilling and threshing equipment, high yield varieties of seeds, or some other inputs that will improve productivity and production (Anang, 2017; Shittu, 2014). Higher agricultural productivity and production increases the amount of marketable agricultural surplus. Hypothetically, off-farm incomes can influence crop sales differently during negative consumption shocks. If there is no surplus agricultural production and household members engage in off-farm activities to contribute to the household's off-farm income pool, then the household may preserve the seed crop at its disposal for the next cropping season and draw on the off-farm pool of income to mitigate the fall in consumption.

Small farms operate on about 12 percent of the world's agricultural land. In SSA, over 80 percent of farms is small (less than 2 ha) and operate on about 40 percent of the agricultural land (Lowder et al., 2016). In Ethiopia, the average farm size is less than a hectare and about 74 percent of the farmers are smallholders[47] who contribute more than 25 percent to the national food production (Rapsomanikis, 2015). The smallholder farm sector contributes to employment and agricultural production in a big way and is hence the focus of this study. Land is the most important asset that households own. However,

[47] Source: FAO small family farms country facts. Available at: http://www.fao.org/3/i8911en/I8911EN.pdf

its role as a source of livelihood and asset has been overshadowed by the land policies that have been pursued in Ethiopia. Its distribution has increasingly become fragmented (Bachewe et al., 2016). In addition to smallholder rural households, many more rural households remain landless. Therefore, studying and understanding the plight of the smallholders and the landless will help address the objective of bringing more people out of poverty.

In Ethiopia, the debate over agricultural commercialization is not new. It has been recognized in various policy documents since the 1950s (Sharp et al., 2007). However, the results have been poor except for a few breakout products such as coffee, khat, and pulses (EEA, 2017). Smallholder production has predominantly been for consumption. The Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (MOFED, 2006) and subsequent development policies[48] have embraced agricultural commercialization as a pathway to poverty reduction. But agriculture is yet to fully deliver on that promise as poverty remains high (OPHI, 2018; Shepherd et al., 2018) and the level of urbanization is the lowest even by SSA standards (Mellor, 2017; Mellor & Dorosh, 2010).

1.2. Motivation and contribution

If improvements in rural households' quality of life are to be achieved, members have to engage in exchange of goods and services. This requires the production of a surplus above and beyond what is needed for subsistence. Households may also engage in selling their agricultural produce even if they do not have a surplus. Such a situation occurs when households are strapped for cash for basic non-food consumption needs such as health. Studies also show that small commercial farms produce the bulk of agricultural output while smallholders form a bulk of rural households but contribute a disproportionately meagre share to the national agricultural output. It is, therefore, argued that transitioning these predominantly subsistence smallholder farm families to small commercial farms will boost economic growth (Mellor, 2017; Mellor & Malik, 2017). Therefore, it is imperative to understand the conditions that determine crop sales and, in particular, what factors drive rural households to participate in agricultural commercialization and when they do what drives the amount of crops offered for sale in the market.

Previous studies analyzing the relationship between agricultural commercialization and off-farm income generating activities have focused on agricultural productivity effects of off-farm incomes. These studies have used various approaches for establishing the presence of a causal relationship running from off-farm incomes to agricultural commercialization. They show mixed results of the effects of off-farm incomes on agricultural productivity. Anang (2017) and Bayissa (2010) show a positive effect of off-farm participation and off-farm incomes on agricultural productivity. Amare and Shiferaw (2017), on the other hand, found a negative relationship between off-farm incomes and agricultural productivity. What has not been studied as much in literature is the effect of off-farm engagement and the income thus earned on agricultural commercialization. Maintaining Boserup's (1965) argument that rural households operate efficiently given their circumstances, a push for commercializing farming can be a less risky economic activity than moving into the unfamiliar like new off-farm activities. This

[48] The Poverty Reduction Strategic Papers (PSRPs).

study adds to the scant literature available on agricultural commercialization and off-farm incomes among rural smallholder and landless households.

This study has the following key contributions. First, it reframes the conceptual underpinning for choosing a causal identification method. Previous studies argue that the decision problem of off-farm participation has a corner solution as an optimum (Nkegbe et al., 2018; Woldeyohanes et al., 2017). However, there is plenty of evidence indicating otherwise. Households decide to engage in off-farm activities not only because they view these as an investment but also because of certain characteristics that they exhibit such as their entrepreneurial predisposition or their risk-taking behavior. Therefore, at a given off-farm marginal income one household may decide to participate in an off-farm activity while another may abstain essentially because of the unobserved heterogeneity among households. This study conceptualizes a decision to participate in off-farm activities as a decision with incidental truncation and not censoring – incidental truncation because the households for which we cannot observe crop sales data could have generated positive, zero, or even negative incomes had they chosen to engage in crop sales. Those households that would likely have a negative sales income choose not to engage in crop sales and hence they self-sort into not participating in crop sales. Second, this study looks at the heterogeneity of the effects of off-farm incomes on household agricultural commercialization based on land ownership. It also tests the sensitivity of the results by using sales of staple crops. Finally, a household's labor supply decision for taking part in off-farm activities is studied within the non-separable consumption and production decision framework. In this respect, this study falls within the realm of a growing body of empirical work that assumes household consumption and production non-separability.

The general objective of this study is looking at the effects of off-farm incomes on agricultural commercialization in rural Ethiopia among smallholders and landless households. Specifically, it measures the effects of engaging in off-farm income generating activities and the incomes thus earned on agricultural commercialization.

The rest of this paper is organized as follows. Section 2 provides a review of key theoretical, methodological, and empirical literature on the relationship between off-farm incomes and agricultural commercialization. Section 3 discusses the data used for the study, the conceptual framework, and the empirical strategy used. Section 4 has a systematic discussion of the findings of the data analysis. The final section provides a summary of the key findings of the study and what these mean for policy.

2. Literature review

Traditionally, the rural off-farm sector has been viewed as a low productivity sector even though households continue to engage in it. Various authors have theoretically explained households' decisions to engage in off-farm activities even in the face of unfavorable odds. Barrett et al. (2001) suggest that households engage in off-farm activities either as an investment decision or as a consumption decision. As an investment decision, households do a cost benefit assessment of engaging in off-farm activities relative to agriculture given their current endowments. As long as the marginal returns to an off-farm activity are higher than those that would have been obtained in agriculture, they choose to opt for the off-farm activity. On the consumption side, a household decides to participate in an off-farm activity if production from the main economic activity of the household, which is agriculture, does not meet its food and non-food consumption requirements. In this respect, engaging in off-farm activities is better positioned to guarantee a more liquid source of income in the form of cash, and this can easily be exchanged for consumables not produced within the household.

Rural households in SSA are still engaged in subsistence agriculture and various attempts to move them to commercial agriculture and out of poverty have met with limited success. As famously indicated by Boserup (1965), this is not irrational behavior on the part of these rural households but a rational response given the constraints they face and the experiences they have. Incomes from non-farm activities may play an important role in improving agricultural productivity by relaxing the liquidity constraints faced by households to buy much needed inputs. This is particularly important for rural households who operate in missing or fragmented credit markets (Adjognon et al., 2017; De Janvry & Sadoulet, 2001). The same studies also showed that farmers used income from crop sales for financing farm input purchases. Non-farm participation could open opportunities for farmers to develop market networks that will expose them to better information on available markets for their agricultural surplus and also get better prices.

Literature also shows that incomes from off-farm sources could also play an indispensable role in contributing to improved agricultural production. This argument proceeds as follows. Rural households are usually cash strapped and face a narrow set of borrowing options due to the undeveloped and fragmented credit markets (Adjognon et al., 2017; Udry & Conning, 2007). In the face of restricted or highly costly credit sources, incomes from off-farm activities, however low paying they may be, provide much needed agricultural 'external inputs'[49] such as more productive seed varieties, agricultural equipment (tilling, weeding, harvesting, and threshing), fertilizers, or even expert advice. Hence, off-farm incomes can be used for improving agricultural productivity which will subsequently lead to agricultural commercialization.

The impact of incomes from off-farm sources on agricultural commercialization, however, is conditional on surplus agricultural production. Studies show that off-farm agricultural activities complement agricultural production and productivity (Babatunde, 2015; Bayissa, 2010; Bezabih et al., 2010; Nedumaran, 2013a; Oseni & Winters, 2009; Pfeiffer et al., 2009). However, some empirical studies find a competing effect of off-farm engagement on farm production and productivity (Amare & Shiferaw, 2017). This competing relationship exists because participation in off-farm activities takes agricultural labor that has a positive marginal productivity away from agriculture.

The link between agricultural sales and off-farm incomes is also documented in literature. For example, Tudor and Balint (2006) found a very strong correlation between off-farm incomes and sale of agricultural produce in Romania. A more recent study from Ghana (Nkegbe et al., 2018) showed that non-farm participation improved agricultural commercialization. The explanation for such effects of off-farm incomes on crop sales is in part linked to marketable agricultural surplus generation. If the marginal increment in productivity is large enough due to off-farm incomes, a household may put part of that increase as marketable surplus. In theory, this surplus could be directed to consumption, thus improving the household's well-being in the short term or it can be invested ensuring long run improvements in its well-being.

There are a lot of works that study the associations and correlations between off-farm incomes and agricultural commercialization. However, attaching causal meanings to these results is often not possible due to the endogenous nature of the decision to engage

[49] The term was coined by Kherallah et al. (2002).

in agricultural commercialization and the income thus earned. Literature shows two sources of potential endogeneity. First, households' decision to participate in market crop sales is endogenous because it usually depends on unobservable household characteristics such as entrepreneurial skills and a tendency for taking risks. Second, the causal relationship between off-farm incomes and crop sales is potentially simultaneous. More income from off-farm sources could improve a farm household's ability to purchase more agricultural inputs and hence result in higher farm production. This could yield higher agricultural surplus and subsequently more income from crop sales. On the other hand, higher income from crop sales could enable household members to enjoy more non-food consumption such as education and health and of better quality. As a result, individuals may be more productive both in their farm and off-farm engagements. It is also possible that the more marketable surplus there is, the more funds households will have which will free more household members for the off-farm labor market. Hence, OLS coefficient estimates of the effects of off-farm incomes on crop sales will be meaningless.

In response to these potential sources of endogeneity, studies have attempted to identify causal relationship between off-farm incomes and agricultural commercialization using different econometric approaches. Woldeyohanes et al. (2017) studied smallholder crop commercialization by controlling for unobserved heterogeneity through a correlated random effects procedure and a double hurdle implementation to adjust for left censoring of off-farm incomes at zero and found that off-farm incomes had no impact on crop sales. However, when conditioned on market participation, the effect became negative indicating that off-farm income generation reduced sales of marketable crop surpluses in rural Ethiopia. Even though the attempt to control for endogeneity was an improvement, the use of a double hurdle model assuming the censoring of off-farm incomes at zero was problematic.

This study argues that the censoring of off-farm incomes is incidental. The unobservable part of off-farm incomes is not because non-participants could not earn incomes from off-farm sources (left censoring at zero), but because households self-sort themselves non-randomly into off-farm participation. This could, for example, mean that households that would otherwise have participated in off-farm activities would have incurred a loss by participating in off-farm income generating activities. This study argues that households decide not to participate in the first place because of an a-priori knowledge of their natural inabilities of making a profit from off-farm engagements.

A study conducted in Nigeria found that off-farm incomes played a positive role in agricultural commercialization (Okezie et al., 2012). However, the authors failed to account for the endogenous nature of off-farm participation. Hence, this positive relation cannot be interpreted as a causal relationship.

Another study from Georgia used a two-level empirical model to study the effects of off-farm incomes on agricultural commercialization of smallholder farmers, specifically crop sales (Kan et al., 2006). The study found that non-farm incomes affected market participation negatively. The authors explicitly modeled the effect of farm output and off-farm incomes on agricultural commercialization using instrumental variables. A major drawback of their study relates to their identification approach as they failed to establish the validity of their instruments both for farm output and non-farm incomes.

A more recent work by Nkegbe et al. (2018) in Ghana, on the other hand, found that non-farm participation increased the amount of crops sold. The authors used a generalized structural equation model (GSEM) for identifying the effects of off-farm participation on smallholder agricultural commercialization through agricultural productivity.

3. Methodology

3.1. Data source and variables

This study uses all three waves of the Ethiopian Socioeconomic Survey (ESS) done under the World Bank Living Standards Measurement Study (LSMS-ISA) project. The survey followed 3,639 rural households in the first wave and expanded the sample to include major urban centers in the subsequent two rounds. ESS covered a period of six years. This study uses a sub-sample of the ESS data specific to smallholders[50] who cultivated less than 2 hectares of land and households that did not participate in cultivation. As a result, the sample size was reduced to 8,622 with 2,874 in each of the three waves after balancing. The variables for the study were identified based on previous literature (Nkegbe et al., 2018; Woldeyohanes et al., 2017). Household demographics, farm production, assets and other endowments, non-farm participation, off-farm incomes, and locational variables are included in the analysis. The outcome variable, agricultural commercialization, is proxied by the value of the crops[51] sold by a household over a period of 12 months before the survey, adjusted for adult equivalent units. The key independent variable, off-farm incomes, is calculated as income from participating in small family run businesses, wage employment (skilled and unskilled), remittances, rents, profits, and sources other than agriculture and livestock. All income values are converted to their real values using the price index provided with the ESS data. Table 5.1. Definition and measurement of variables used in the study gives a summary of the variables used in the study.

Table 5.1. Definition and measurement of variables used in the study

Variables	Definition and measurement
Participates in crop sales	If a household participates =1 and 0 otherwise
Crop sales (ETB)	Real value of 17 non-permanent main crops[52] sold in Br. by a household
Sex of head	Male = 0, female = 1
Age of head	In years
Household size	Head count
Schooling of head	In years
Off-farm participation	If a household participates =1 and 0 otherwise
Off-farm income	Real value of income from activities other than farming and livestock
Crop produced	Real value 12 main non-permanent crops produced by a household
Participates in extension program	If a household participates =1 and 0 otherwise

[50] The definition of smallholders is borrowed from Lowder et al. (2016) and Hazell et al. (2010).

[51] The crop values were calculated for 12 non-permanent crops which included all the main staples. Village level prices were used to impute values and where these were not available averages from higher geographical aggregations were used. The values were converted to real equivalents using price indices provided with the ESS data.

[52] These are teff, wheat, barley, sorghum, millet, enset/ kocho, coffee, field peas, haricot, lintel, horse bean, niger seed (nueg), chickpeas, khat, onion, banana, potato.

Participates in irrigation	If a household participates =1 and 0 otherwise
Elevation	In meters above sea level
Land owned (Ha.)	In hectares
Livestock owned	In tropical livestock units as in Storck et al. (1991)
Asset index	Normalized first principal component of 39 asset ownership indicator variables
Nearest market	In km
Nearest asphalt road	In km
Nearest MFI	In km
Region	a dummy variable representing five regions: 1 = Tigray, 2 = Amhara, 3 = Oromia, 4 = SNNP and 5 = Other regional states

Source: author's construction using ESS data.

3.2. Conceptual framework

This study uses the basic non-separable farm household model (Singh et al., 1985) to derive relations in the form of reduced form equations for off-farm participation and crop sales. The non-separable model assumes that household consumption and production decisions are not separable because the markets for products and labor are imperfect. This study uses a rendering of the non-separable farm household model in Woldeyohanes et al. (2017) to conceptualize the relationship between off-farm incomes and sale of agricultural produce.

Consider a household maximizing utility with respect to consumption, c_j; production, q_j; production inputs, k_l; sales, s_j; and purchase, b_j, of each good $j=1,2,...,M$ and inputs $l=1,2,...,N$. Agricultural goods produced by the household, goods bought from the market, and leisure constitute these M goods. The household produces agricultural goods, q_j, using production inputs (land, labor, and other variable inputs), k_l. The household, therefore, maximizes utility subject to liquidity (5.2), commodity balance (5.3), production technology (5.4), and non-negativity (5.5) constraints:

(5.1) $$\max_{q_j, s_j, b_j, c_j, k_l} U\left(c, z_u\right)$$

Subject to:

(5.2) $$\sum_j p_j^m \left(s_j - b_j\right) - \sum_l p_l k_l + w \geq 0$$

(5.3) $$q_j - k_j + E_j - c_j + b_j - s_j \geq 0 \quad for \quad j=1,...,N$$

(5.4) $$G\left(q_1 ... q_N, k_1, ..., k_N; z_q\right) = 0$$

(5.5) $$q_j, s_j, c_j, k_l \geq 0; \quad for \quad j=1,...,N \quad and \quad l=1,...,M$$

where p_j^m is the market price of commodity j; p_l is the per unit cost of production inputs; E_j is the endowment of commodity j; w is the off-farm income; and z_u and z_q are vectors of household demographics and production characteristics respectively. The liquidity constraint states that the amount of commodity and input purchases cannot exceed the income a household gets from agricultural sales and off-farm incomes. The commodity balance constraint states that the total quantities consumed, used as inputs and supplied to the market are less than or equal to the total quantity produced, endowed and purchased from the market for each commodity. The production technology in this optimization is well behaved.

The first order conditions of the maximization problem of the utility function will yield the reduced form output market supply conditional on market participation. Output market participation decision is given by:

(5.6) $$q_{sj}^{p} = f\left(p_j^m, z_u, z_q, w\right)$$

And sale of agricultural produce can be modeled as:

(5.7) $$q_{sj} = f\left(p_j^m, z_q, w\right)$$

3.3. Empirical strategy for causal identification

Households' decision to participate in crop sales is non-random. This results in an incidental truncation of the income a household generates from engaging in agricultural commercialization. Therefore, regression coefficients must be corrected for this self-selection bias. Another source of endogeneity of off-farm incomes is the possibility of reverse causation running from crop sales to off-farm incomes. This study addresses both sources of endogeneity. It assumes that the unobserved source of heterogeneity that jointly determines the differences in households' abilities to generate incomes from off-farm activities and crop sales are time invariant. Hence, it controls for this heterogeneity through a random effects (RE) regression (Wooldridge, 2010) of the outcome equation. This assumption appears to hold since the sources of correlation between the selection equation and the outcome equation are statistically significant for the time invariant component of the error terms (see Table 5.5).

The potential selection problem is corrected by using a Heckman (1979) correction procedure modified for panel data and using lagged values for off-farm incomes which is suspect for endogeneity with crop production and sales. This paper conceptualizes censoring of income from crop sales not as naturally occurring but as incidental associated with a household's decision not to market its agricultural produce. This kind of censoring results in a selection bias. The selection bias can be corrected by conditioning on observables and unobservables. To address both unobserved heterogeneity and self-selection at the same time and also accounting for the panel structure of the data, this paper adopts the approach followed in Bartus and Roodman (2014). Even though the estimation is done simultaneously using maximum likelihood, there are two parts of the estimation problem. In the first step, the decision to sell crops in the market is modeled as:

(5.8) $$\Pr\left(q_{sj} = 1 \mid z_u, z_q, w\right) = \Phi(z_u, z_q, w)$$

$\Phi(.)$ is the cumulative density function of the normal distribution. When the panel structure of the data is considered, this can be equivalent to a control function given as:

(5.9) $$s_{it} = 1\left(z_{it}\alpha + v_{1t} + \varepsilon_{1it} > 0\right)$$

where $s_{it} = 1$ if the household engages in crop sales and 0 otherwise. z_{it} is a vector of off-farm incomes, off-farm participation, and other covariates' modeling selection. ν_{1t} is the panel level random effect and ε_{1it} is the observation level selection error.

In the second step, the selection bias is corrected by incorporating the transformed predicted probabilities from Equation (5.9) and including them as additional explanatory variables in the outcome equation as:

(5.10) $$q_{sj} = f\left(z_q, w, \hat{q}_{sj}^{p}\right)$$

The empirical specification accounting for the panel structure of the estimation is given as:

(5.11) $$y_{it} = x_{it}\beta + \nu_{2i} + \varepsilon_{2it}$$

where y_{it} is crop sales of household i in wave t. x_{it} is a vector of off-farm incomes and participation and other covariates modeling crop sales. ν_{2i} is the panel level random effect and ε_{2it} is the observation level error. The vectors α and β are parameters to be estimated. This procedure assumes that the random effects ν_{1t} and ν_{2i} are bivariate normal with mean zero and variance:

(5.12) $$\begin{bmatrix} \sigma_{1\nu}^2 & \rho_\nu \sigma_{1\nu}\sigma_{2\nu} \\ \rho_\nu \sigma_{1\nu}\sigma_{2\nu} & \sigma_{2\nu}^2 \end{bmatrix}$$

and the observation level errors ε_{1it} and ε_{2it} are also bivariate normal with mean zero but variance:

(5.13) $$\begin{bmatrix} \sigma_1^2 & \rho\sigma_1 \\ \rho\sigma_1 & 1 \end{bmatrix}$$

4. Results

4.1. Descriptive results

The study sample constitutes rural smallholders who cultivated less than 2 hectares of land (76 percent or 6,513 households) and households who did not cultivate (24 percent or 2,109 households). On the other hand, 87.4 percent (7,534 households) owned land while the remaining households (1,088 households) did not (refer to Table 5.2). All households that produced crops, cultivated their own land. However, not all households in the study sample who owned land cultivated it. This is reflected in Table 5.2. Among households who owned land, 13.5 percent (1,021) did not cultivate it. All households who cultivated owned the land. Hence, smallholders in the sample cultivated their own land.

Table 5.2. Land cultivation versus land ownership

Household …		Owns land		
		No	Yes	Total
cultivates land	No	1,088	1,021	2,109
	Yes	0	6,513	6,513
	Total	1,088	7,534	8,622

Source: Author's calculations using ESS data.

There is a marked difference between households who engaged in agricultural commercialization and those who did not. Among the sampled households, 2,236 households or 26 percent engaged in agricultural commercialization (see Appendix 5.1). Table 5.3 gives a summary of the different variables used in the study based on whether they sold part of their crop production in the market.

Table 5.3. Summary statistics by crop sales[53]

Variables	Do not sell crops in the market			Sell crops in the market			Diff.[54] (Δ)
	Mean	St. dev.	N	Mean	St. dev.	N	
Crop sales (engage=1)	0.00	0.00	6,391	1.00	0.00	2,231	1.00**
Crop sales income	0.00	0.00	6,391	311.97	574.51	2,231	311.97**
Crop produced	526.10	1,534.97	6,391	1,584.31	4,408.50	2,231	1,058.21**
off-farm (participates =1)	0.66	0.45	6,391	0.53	0.50	2,231	-0.13**
Off-farm income	4,524.72	58,655.12	6,391	1,167.38	9,469.04	2,231	-3,357.34**
Sex of head	0.27	0.47	6,355	0.19	0.40	2,228	-0.08**
Age of head	46.04	16.11	6,357	45.30	14.78	2,228	-0.74
Household Size	4.75	2.38	6,391	5.01	2.06	2,231	0.26**
Schooling of head	2.38	4.11	6,288	1.53	2.65	2,209	-0.85**
Land owned (ha.)	0.56	1.82	6,391	1.06	0.65	2,231	0.50**
Livestock owned (TLU)	1.91	3.59	6,391	2.71	11.60	2,231	0.80**
Asset index	-0.65	2.49	6,391	-1.03	2.46	2,231	-0.38**
Elevation (m)	1,983.33	620.07	6,364	2,091.73	517.28	2,228	108.40**
Extension services	0.23	0.38	6,391	0.46	0.49	2,231	0.23**
Irrigation	0.07	0.28	6,391	0.10	0.31	2,231	0.03**
Nearest market	37.21	62.42	6,391	37.88	52.77	2,231	0.67
Nearest asphalt road	6.03	19.49	6,391	5.48	12.44	2,231	-0.56**
Nearest MFI	11.52	22.61	6,391	13.73	19.02	2,231	2.21**

Note: * = p< 5% and ** = p< 1% statistics calculated as mean differences (participants – non-participants) on pooled data.

Source: Author's calculations using ESS data.

[53] Income variables are calculated as real values and are adjusted for household size in adult equivalent units. The statistics are also weighted using survey sampling weights.

[54]The mean differences are calculated as the difference between the mean of households that sell crops less households that do not sell their crops.

The mean income from crop sales was ETB 311.97. Among households who engaged in crop sales, 19 percent were female headed while 27 percent households were female headed among those who did not engage in crop sales. The difference in the share of female headed households among those engaged in crop sales and those who were not is statistically significant. The average age of the household head was 45.3 years for households engaged in crop sales. It was about 46 years for those who were not. The age difference between the two groups was not statistically discernible. A household that engaged in crop sales had 5.01 members on average. This is 0.26 more members than households that did not engage in crop sales. Though the difference is small, it is statistically significant. The average years of schooling of a household head that participated in crop sales was 1.53. This was 0.85 years less than that for those who did not participate in crop sales. The level of education of the household heads in both categories means that they did not have basic literacy and numeracy skills.

In terms of off-farm incomes, households engaged in crop sales were out-earned by households that did not engage in crop sales. The average off-farm incomes from participating in off-farm activities[55] was ETB 1,167.38. This was ETB 3,357.34 less than the income that households who did not engage in off-farm activities earned. This points towards the possibility that households may be choosing one or the other but not both.

In terms of just participation in off-farm income generating activities, households which were not engaged in crop sales had higher participation rates relative to those who were engaged in crop sales. Among those not engaged in crop sales, 66 percent participated in off-farm activities while among those who did 53 percent participated in off-farm activities.

Crop production also showed statistically significant difference by a household's engagement status in crop sales. Households that engaged in crop sales produced ETB 1,584.31 while those which did not engage in crop sales produced ETB 526.10. This means that the households engaged in crop sales produced more crop valued at ETB 1,058.21. The same households also had higher participation rates in agricultural extension programs (a difference in participation rates of 23 percent).

Households that engaged in crop sales owned more land ($\Delta = 0.50$ ha) and livestock ($\Delta = 0.8$[56] TLU) but less assets ($\Delta = -0.38$). As one would expect, households that sold crops in the market owned more land which translated into more cultivated land. Households who engaged in crop sales owned more livestock relative to those who did not engage in crop sales.

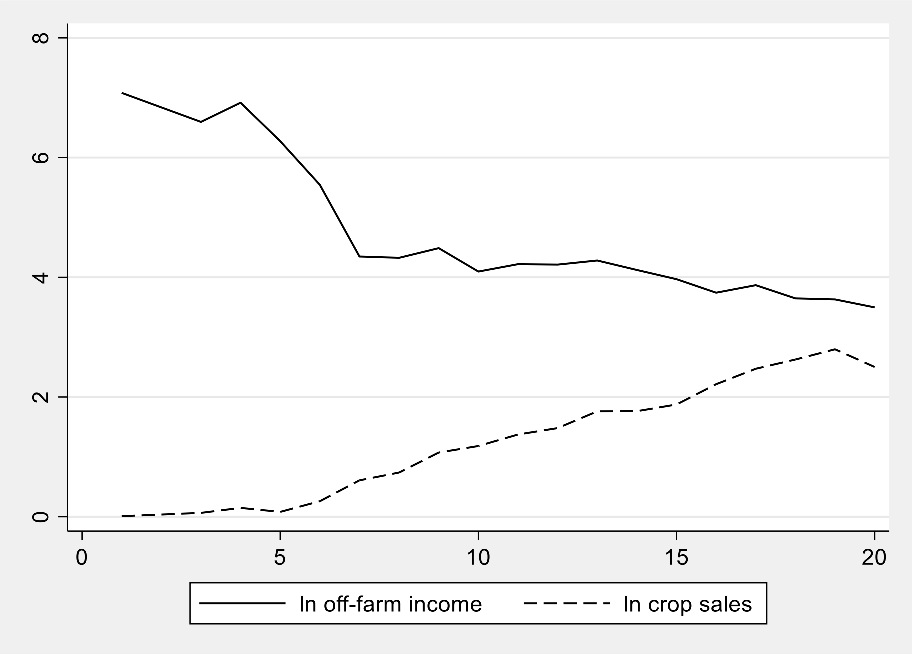
4.2. Crop sales and off-farm activities

This study is concerned with the effects of off-farm participation and the incomes thus earned on agricultural commercialization among rural households. This sub-section discusses the relationship patterns between households' off-farm activities and crop sales behavior by examining the correlations and associations between the two. Literature indicates that the relationship between off-farm incomes and crop sales can be positive (Abdullah et al., 2019; Okezie et al., 2012), negative (Kan et al., 2006), or non-existent (Woldeyohanes et al., 2017).

[55] These are identified as family enterprises, skilled wage employment, unskilled wage employment (casual labor and PSNP employment), interest on savings, profits, and rents.
[56] This is equivalent to one horse (Storck et al., 1991).

Figure 5.1 plots the incomes from off-farm activities and crop sales against 20th percentile household land ownership categories. The incomes from these two sources appear to move in opposite directions relative to household land ownership.[57] As one goes up the land ownership 20th percentiles, incomes from crop sales increase while incomes from off-farm activities fall. Note that this result is for households that cultivate less than 2 hectares of land or do not own any land for cultivation. This relationship strengthens the results in Table 5.3 which shows that there is a trade-off between incomes from crop sales and off-farm activities. However, since this relationship does not account for the panel structure of the data and also does not correct for potential sources of endogeneity in the relationship, it is too early to definitively assert that there is a trade-off between the two income sources or that off-farm income sources and crop sales are substitutable as asserted in Kan et al. (2006).

Figure 5.1 also shows that households at every 20th percentile category earned more incomes from off-farm activities than from crop sales; however, this income difference decreased as the percentile category increased.



Source: author's calculations using ESS data

Figure 5.1. Off-farm incomes and crop sales plotted against 20th percentiles of land owned

The graph given in Figure 5.1 is further confirmed using a formal test of association and correlation reported in Table 5.4. Panel A of Table 5.4 reports Pearson's χ^2 statistic as a measure of association between the decision to participate in off-farm income generating activities and crop sales. The results show that there is a strong association ($\chi^2(1)$ = 204.58; p = 0.000) between the two. Panel B of Table 5.4 gives Pearson's correlation

[57] A similar result is observed when the reference of comparison is value of crop production instead of land ownership (see Appendix 5.2).

coefficient (ρ = -0.018; p = 0.102) between incomes from crop sales and off-farm incomes. The coefficient is not statistically different from zero. Therefore, there is no correlation between the two sources of income, per se. This result contrasts the visual relationship given in Figure 5.1. A potential non-random selection could be the culprit for this mismatch between the statistics and the figure. One evidence in support of this view is the fact that the difference in the mean off-income between households who engaged in crop sales and households that did not is statistically significant (refer to Table 5.3).

Table 5.4. Off-farm activities and crop sales

Panel A: Association of participation decisions				
Household …		Participates in off-farm activities		
		No	Yes	Total
Sales crops	No	1,816	4,575	6,391
	Yes	1,002	1,229	2,231
	Total	2,818	5,804	8,622
Pearson's χ^2 (1) = 204.58, p-value = 0.000				

Panel B. Correlation of income (Pearson's correlation coefficient)		
	Crop sales	Off-farm
Crop sales	1.000	-
(p value)	-	-
Off-farm	-0.0176	1.000
(p value)	(0.1019)	
N=8,622		

Source: Author's calculations using ESS data.

4.3. Econometric results

This sub-section discusses the presence of a causal effect of participation in off-farm activities and the incomes thus earned on the volume of crop sales accounting for potential selection bias of households for agricultural commercialization and reverse causality running from crop sales to off-farm participation and incomes due to household specific characteristics. As the main model of the analysis, it uses a Heckman selection model with a random effects (RE)[58] specification of both the outcome and selection equations where off-farm participation and income enter the regression with a one period lag. This accounts for the panel structure of the data, corrects for households' non-random decisions to participate in crop sales, and avoids the reverse causal effects of agricultural commercialization on off-farm participation and incomes.

[58] The Stata version 16 module *-xtheckman-* was used for this implementation where household specific unobservables were treated as random in both the selection and outcome equations.

For the purposes of comparison, a Heckman model is also estimated without taking the lags of off-farm participation and income variables. Coefficients of a fixed effects (FE) regression are also reported. The use of a FE regression assumes that the sources of non-random selection and other sources of endogeneity are time invariant household fixed effects. A FE estimator removes these unobservable FEs.

Table 5.5 gives the regression coefficients for FE (Column 1) and two RE Heckman regressions – one with lagged off-farm participation and income variables (Columns 4 and 5) and another where off-farm participation and income enter without lags (Columns 2 and 3). The selected model-fit statistics are reported at the bottom of the table. The results show that off-farm incomes had no effect on agricultural commercialization in all three regressions. However, off-farm incomes had a negative effect on a household's decision to engage in crop sales (Columns 3 and 5). An increase in a household's off-farm incomes by 1 percent lowered its probability of participating in crop sales by 0.139 percent. These two results together mean that more off-farm incomes discouraged a household from engaging in agricultural commercialization, and it had no effect on crop sales. In a household's decision set, off-farm incomes can be thought of as a substitute for incomes from agricultural commercialization which may be why the result shows that households tend to shift away from agricultural commercialization as their off-farm incomes increase. Previous studies have also arrived at a similar result of no relation between off-farm income and crop sales using different methodologies (Woldeyohanes et al., 2017). Other studies, however, showed negative effects (Kan et al., 2006) but without the proper methodology to account for non-random self-selection of households into agricultural commercialization.

The decision to participate in income generating off-farm activities is the other key variable of interest in this study. A household's decision to participate in off-farm income generating activities has a positive effect on its probability of engaging in crop sales but has no effect on the amount of crops sold. Nkegbe et al. (2018) report a similar result. Looking at Column 5 of Table 5.5, a household's participation in off-farm activities increases its probability of engaging in crop sales by 0.733 percent.

As expected, household crop production had a positive and statistically significant effect on its decision to engage in crop sales and the level of crops sold in the market. An increase in a household's crop production by one percentage point resulted in an increase in the probability of it engaging in crop sales by 0.219 percent. A one percentage point increase in crop production increased the amount of crops a household sold by 0.165. This result remained robust in the implementation of the Heckman selection model without lags and the fixed effects regression. Similar results are reported in previous studies (Nkegbe et al., 2018; Woldeyohanes et al., 2017).

Female headed households had a lower probability of participating in agricultural commercialization relative to male headed households. In probability terms, a female headed household was 0.225 percent less likely to participate in crop sales relative to a male headed household in rural Ethiopia among smallholders and those who did not own land. Woldeyohanes et al. (2017) arrived at a similar result.

Age of the household had a negative, statistically significant coefficient. This means that households with older heads were less likely to engage in agricultural commercialization and tended to generate smaller incomes from crop sales if they did engage in crop sales. However, the age effect was very small. A household's probability of engaging in crop sales fell by 0.005 percent for each additional year of a household head's age. When a household head's age increased by one more year, its crop sales amount fell by 0.00 percent. This result confirms the findings of previous studies (Nkegbe et al., 2018).

Household size was found to have no effect on the decision to engage in agricultural commercialization, but a negative and statistically significant effect on the volume of crops sold in the market. An addition of one more household member would result in a fall in the amount of crops sold by 0.092 percent. Since households in the rural parts of developing countries like Ethiopia end up consuming a large share of their agricultural produce the negative sign of the coefficient is no surprise. A bigger household size means more mouths to feed and hence this will likely reduce the agricultural surplus available for commercialization. Another explanation is looking at the household size as a driver of consumption and income diversification (Barrett et al., 2005; Woldehanna & Oskam, 2001).

Schooling of the household head was not found to have a positive and statistically significant effect on crop sales and on a household's decision to engage in crop sales. The insignificant effect of a head's schooling on the decision to participate in crop sales and the volume of crop sales appear to be surprising at first glance. However, other studies also report similar results (Kan et al., 2006; Woldeyohanes et al., 2017). Accounting for intra-household dynamics of education may give a different picture of the role of education in agricultural commercialization of rural households.

Land and livestock ownership had positive and significant effects on crop sales. In particular, the coefficient of livestock ownership had a positive and statistically significant effect both on a household's decision to engage in crop sales and on the income generated from crop sales. Asset ownership, however, had a negative effect on a household's probability to engage in agricultural commercialization. These results are partly in conformity with previous studies (Woldeyohanes et al., 2017).

Among different agricultural practices adopted by households, benefiting from agricultural extension services had a positive and statistically positive effect both on a household's decision to participate in crop sales and on the amount of crops sold. If a household received an agricultural extension service, its probability of participation in crop sales increased by 0.301 percent and the amount of crops it sold increased by 0.239 percent. This is testament to the importance of agricultural extension services as documented in previous studies (Nkegbe et al., 2018).

The use of a random effects Heckman selection model is clearly justified as the correlation of the idiosyncratic and household specific error structures between the selection and outcome equations is statistically significant. The correlation between the errors of the selection and outcome equations (ρ_v and ρ_e) are significant in both implementations of the Heckman model on the selection structure. Hence, households' self-sorting into those who sell crops and those who do not is non-random, as initially suspected. Further, the RE model shows that the error correlation is significant between household specific errors (ρ_v) and not between idiosyncratic errors (ρ_e). This further shows that the source of selection is time invariant and the endogeneity of off-farm incomes is also likely to be due to these time invariant unobservables. The Wald test shows the selection and outcome equations in both cases of the Heckman selection model's implementations indicate that the two selection and outcome equations are not independent. To ensure identification of the model, two variables used in the selection equation – distance to the nearest asphalt road and distance to the nearest microfinance institution (MFI) – were excluded from the outcome equation. These variables were used since they affect a household's decision to engage in crop sales but not the volume of crops sold.

Table 5.5. The FE and Heckman selection regressions

Variables	FE	RE Heckman			
		Without lags		With lags	
	Outcome (crop sales, *ln*)	Outcome (Crop sales, *ln*)	Selection (Sells crop =1)	Outcome (Crop sales, *ln*)	Selection (Sells crop =1)
	(1)	(2)	(3)	(4)	(5)
Off-farm income	0.033	0.017	-0.026***	0.011	-0.139***
	(0.035)	(0.029)	(0.008)	(0.030)	(0.020)
Off-farm participation	-0.177	-0.150	-0.116**	-0.106	0.733***
	(0.218)	(0.185)	(0.053)	(0.190)	(0.136)
Crop value, production	0.034**	0.167***	0.220***	0.165***	0.219***
	(0.015)	(0.022)	(0.010)	(0.022)	(0.010)
Sex, head	0.046	0.002	-0.199***	0.003	-0.215***
	(0.254)	(0.084)	(0.067)	(0.084)	(0.067)
Age, head	-0.006	-0.007***	-0.005***	-0.007***	-0.005***
	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
Household size	-0.034	-0.091***	0.031**	-0.092***	0.023*
	(0.036)	(0.017)	(0.013)	(0.017)	(0.013)
School years, head	0.009	0.010	-0.012	0.011	-0.006
	(0.028)	(0.014)	(0.010)	(0.014)	(0.010)
Owned land	0.210**	0.237***	0.037*	0.236***	0.037*
	(0.096)	(0.071)	(0.022)	(0.070)	(0.022)
Livestock, in TLU	0.000	0.002***	0.015*	0.002***	0.016**
	(0.000)	(0.000)	(0.008)	(0.000)	(0.008)
Asset index, PCA based	-0.005	0.050	-0.150***	0.053	-0.124***
	(0.014)	(0.039)	(0.036)	(0.038)	(0.036)
Extension service	0.185**	0.192***	0.225***	0.190***	0.223***
	(0.080)	(0.069)	(0.060)	(0.069)	(0.060)
Irrigation	0.061	0.096	-0.001	0.095	-0.012
	(0.112)	(0.092)	(0.082)	(0.092)	(0.082)
Distance nearest market	-0.004	-0.008***	0.001	-0.008***	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Distance asphalt road	0.001	-	0.001	-	0.000
	(0.001)		(0.001)		(0.001)
Distance microfinance	0.002	-	0.002	-	0.002
	(0.002)		(0.001)		(0.001)
δ_e		1.043***		1.042***	
		(0.085)		(0.085)	
ρ_e		-0.011		-0.028	
		(0.101)		(0.097)	
δ_v		0.456***		0.442***	
		(0.077)		(0.076)	
ρ_v		0.376***		0.383***	
		(0.129)		(0.131)	

Constant	4.331***	4.157***	-1.649***	4.191***	-1.589***
	(0.538)	(0.386)	(0.210)	(0.380)	(0.205)
F-statistics	7.52				
Wald statistic		230.57		229.86	
R-squared	0.105				
Non-participants		5,689	5,689	5,689	5,689
Participants		2,873	2,873	2,873	2,873
Total observations	8,562	8,562	8,562	8,562	8,562
Households	1,281	1,281	1,281	1,281	1,281

Note: Robust standard errors in parentheses clustered at the household level; p-values reported for F and Wald statistics; *** p<0.01, ** p<0.05, and * p<0.1; outcome = crop sales in ln, selection is measured as an indicator variable with 1 meaning engages in crop sales. Regressions are controlled for regional and panel dummies. Off-farm incomes and participation variables are one period lagged for regressions in Columns 4 and 5.

Source: Author's calculations based on ESS data.

5. Conclusion and recommendations

Commercialization of agriculture is key to uplifting rural smallholder households out of destitution and poverty. This paper studied the effects of participation in off-farm activities and the incomes thus earned on households' decisions to engage in agricultural commercialization and on the incomes generated through such endeavors. As a point of departure with previous studies, this study pinned the source of endogeneity in the decision to engage in crop sales as an incidental truncation and not as censoring at zero sales income. In line with this conceptualization of the selection problem, a Heckman correction procedure was used for correcting the potential self-selection of a household for agricultural commercialization. Moreover, off-farm participation and off-farm income variables were entered into the regression as one period lagged variables to avoid reverse causal effects of crop sales on off-farm participation and incomes. The panel structure of the data was exploited to estimate a variant of the Heckman selection model.

The data for the study came from the Ethiopian Socioeconomic Survey (ESS) which is part of a multi-module, multi-country data collection for better understanding agriculture – LSMS-ISA. The study sample was restricted to households that cultivated less than 2 hectares of land and households that did not own land. These households represent the lower economic strata of rural households and constitute a sizeable majority of rural dwellers in sub-Saharan Africa in general and in Ethiopia in particular. The total sample was 8,622 households about 87 percent of whom owned land. All households who cultivated, cultivated their own land but not everyone who owned land cultivated it. The results of the study showed that households that engaged in agricultural commercialization were different from those who did not in terms of diverse characteristics such as the sex of the household head, household size, schooling of the head, land ownership, livestock ownership, asset ownership, utilization of agricultural extension services and irrigation. The two categories also showed marked differences in terms of crop production, off-farm incomes, and participation rates in off-farm income generating activities.

A visual examination of the relationship between incomes from off-farm activities and crop sales suggested a negative relationship between the two, but a test for correlation returned insignificant. Further, an examination of the association between participating in off-farm income generating activities and crop sales returned a statistically significant result. These seemingly conflicting results are suspect to underlying influence that is not readily apparent either in the visual or the statistical tests. Correcting for selection and reverse causality in the relationship showed that off-farm incomes did not have a statistically significant effect on agricultural commercialization. However, off-farm incomes had a negative effect on a household's decision to engage in crop sales. More off-farm incomes discouraged a household from engaging in agricultural commercialization, but it had no effect on income from crop sales. A household's decision to participate in off-farm income generating activities had a positive effect on its probability of engaging in crop sales but had no effect on the amount of crops sold in the market. A household's amount of crop production had a positive effect on its agricultural commercialization. Female headed households had a lower probability of commercializing their agriculture. A household's age had a small negative effect on engaging in agricultural commercialization. Household size had a negative effect on income from crop sales, as expected. Land and livestock ownership had a positive effect on a household's probability of engaging in agricultural commercialization. Utilization of agricultural extension services had a positive effect both on the probability of participating in crop sales and incomes from crop sales. These results are largely similar to previous findings.

These results point towards some important recommendations for improving the lives of rural smallholder and landless households. First, off-farm incomes are an important variable in households' decisions to engage in crop sales but not in income from such commercialization. Hence, depending on the intention of the policy being pursued, incentivizing off-farm participation should be carefully done depending on the targeted households. The results of this study show that though a household can be nudged into agricultural commercialization through policy incentives that encourage off-farm participation, this does not necessarily guarantee increased incomes from crop sales. In particular, such incentives should be accompanied by other additional nudges such as provision of extension services. Given the paucity of policy and programmatic support for incentivizing engagement in off-farm activities, this study is an important addition to the evidence that off-farm incomes are an important variable in rural household welfare.

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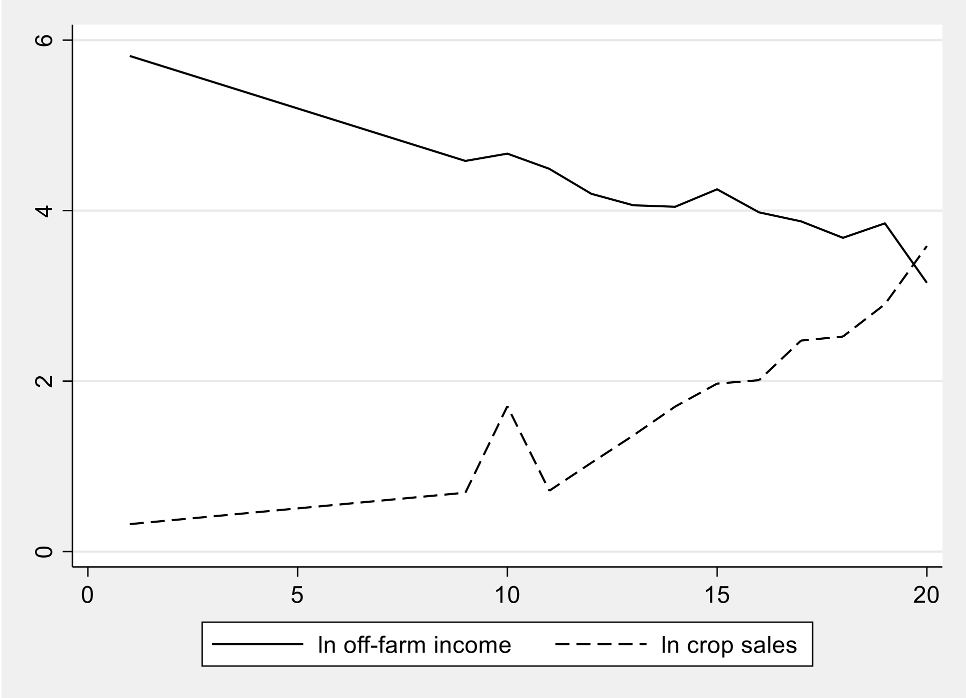
Appendix 5

Appendix 5.1. Summary statistics of the data

Variables	Pooled			2011/12			2013/14			2015/16		
	Mean	St. dev.	N	Mean	St. dev.	N	Mean	St. dev.	N	Mean	St. dev.	N
Crop sales												
Participates in crop sales	0.26	0.44	8,622	0.22	0.42	2,874	0.30	0.46	2,874	0.26	0.44	2,874
Crop sales (ETB)	1,113.85	1,854.26	2,236	715.10	1,077.70	643	1,193.17	2,175.30	858	1,370.10	1,927.77	735
Household demographics												
Schooling of head (yrs.)	2.23	3.81	8,497	2.16	3.67	2,808	2.20	3.80	2,840	2.33	3.95	2,849
Household Size	4.71	2.31	8,622	4.64	2.30	2,874	4.69	2.29	2,874	4.81	2.34	2,874
Age of head	45.69	15.78	8,585	44.18	15.91	2,837	45.65	15.66	2,874	47.22	15.62	2,874
Sex of head	1.29	0.45	8,583	1.28	0.45	2,837	1.29	0.45	2,873	1.30	0.46	2,873
Production characteristics												
Off-farm participation ==1	0.57	0.50	8,622	0.57	0.49	2,874	0.57	0.50	2,874	0.56	0.50	2,874
Off-farm income	5.06	5.43	8,622	5.09	5.40	2,874	5.15	5.55	2,874	4.95	5.34	2,874
Crop produced (ETB)	2,572.48	12,137.18	8,622	865.92	5,083.92	2,874	4,153.87	16,438.79	2,874	2,697.66	11,854.33	2,874
Participates in agriculture extension	0.30	0.46	6,550	0.26	0.45	2,018	0.31	0.46	2,257	0.32	0.47	2,275
Farm characteristics												
Elevation (m asl)	1,832.23	600.86	8,592	1,833.95	602.11	2,844	1,831.04	602.08	2,874	1,831.71	598.60	2,874
Agroecological zones	321.40	3.71	8,592	321.40	3.71	2,844	321.40	3.71	2,874	321.40	3.71	2,874
Wettest quarter temperature (ºC *10)	193.32	39.62	8,592	193.23	39.66	2,844	193.38	39.67	2,874	193.35	39.52	2,874
Nutrient availability	1.44	0.72	8,592	1.44	0.72	2,844	1.44	0.72	2,874	1.43	0.72	2,874
Precipitation in wettest quarter (mm)	544.24	214.96	8,592	544.89	215.10	2,844	543.89	215.00	2,874	543.96	214.85	2,874
Workability	2.78	1.18	8,592	2.79	1.19	2,844	2.78	1.18	2,874	2.77	1.18	2,874
Endowments												
Livestock owned (in TLU)	2.22	6.67	8,622	1.94	3.55	2,874	2.03	3.06	2,874	2.69	10.54	2,874
Asset index First PCA	-0.60	2.49	8,622	0.03	3.66	2,874	-0.99	1.49	2,874	-0.85	1.55	2,874
Land owned (Ha.)	0.63	1.61	8,622	0.56	0.65	2,874	0.70	2.55	2,874	0.62	0.95	2,874
Household cultivates < 2 ha.	0.76	0.43	8,622	0.70	0.46	2,874	0.78	0.42	2,874	0.79	0.41	2,874

Source: Author’s calculations using ESS data.

Appendix 5.2. Off-farm and crop sales' incomes plotted against crop production



Source: based on author's calculation using ESS data

Appendix 5.3. Regression results, FE, Pooled Heckman, and Panel RE Heckman sample selection model

Variables		FE	Heckman			
			without lags		with lags	
		Outcome	Outcome	Selection	Outcome	Selection
		(crop sales, *ln*)	(Crop sales, *ln*)	(Sells crop =1)	(Crop sales, *ln*)	(Sells crop =1)
	Off-farm income	0.033	0.017	-0.026***	0.011	-0.139***
		(0.035)	(0.029)	(0.008)	(0.030)	(0.020)
	Off-farm participation	-0.177	-0.150	-0.116**	-0.106	0.733***
		(0.218)	(0.185)	(0.053)	(0.190)	(0.136)
	Crop value, production	0.034**	0.167***	0.220***	0.165***	0.219***
		(0.015)	(0.022)	(0.010)	(0.022)	(0.010)
	Sex, head	0.046	0.002	-0.199***	0.003	-0.215***
		(0.254)	(0.084)	(0.067)	(0.084)	(0.067)
	Age, head	-0.006	-0.007***	-0.005***	-0.007***	-0.005***
		(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
	Household size	-0.034	-0.091***	0.031**	-0.092***	0.023*
		(0.036)	(0.017)	(0.013)	(0.017)	(0.013)
	School years, head	0.009	0.010	-0.012	0.011	-0.006
		(0.028)	(0.014)	(0.010)	(0.014)	(0.010)
	Owned land	0.210**	0.237***	0.037*	0.236***	0.037*
		(0.096)	(0.071)	(0.022)	(0.070)	(0.022)
	Livestock, in TLU	0.000	0.002***	0.015*	0.002***	0.016**
		(0.000)	(0.000)	(0.008)	(0.000)	(0.008)
	Asset index, PCA based	-0.005	0.050	-0.150***	0.053	-0.124***
		(0.014)	(0.039)	(0.036)	(0.038)	(0.036)
	Extension service	0.185**	0.192***	0.225***	0.190***	0.223***
		(0.080)	(0.069)	(0.060)	(0.069)	(0.060)
	Irrigation	0.061	0.096	-0.001	0.095	-0.012
		(0.112)	(0.092)	(0.082)	(0.092)	(0.082)
Distance	Nearest market	-0.004	-0.008***	0.001	-0.008***	0.001
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
	Asphalt road	0.001		0.001		0.000
		(0.001)		(0.001)		(0.001)
	Microfinance	0.002		0.002		0.002
		(0.002)		(0.001)		(0.001)
Wave	2013/14	0.336***				
		(0.084)				
	2015/16	0.522***	0.434***	0.094**	0.433***	0.101**
		(0.083)	(0.059)	(0.044)	(0.059)	(0.044)
Region	Amhara		-0.049	0.433***	-0.053	0.416***
			(0.150)	(0.100)	(0.148)	(0.099)
	Oromia		0.037	-0.115	0.036	-0.130
			(0.166)	(0.107)	(0.166)	(0.107)
	SNNPRS		-0.057	0.277***	-0.061	0.257***

			(0.147)	(0.098)	(0.146)	(0.097)
	Others		0.353**	-0.561***	0.357**	-0.536***
			(0.178)	(0.116)	(0.177)	(0.116)
δ_e			1.043***		1.042***	
			(0.085)		(0.085)	
ρ_e			-0.011		-0.028	
			(0.101)		(0.097)	
δ_v			0.456***		0.442***	
			(0.077)		(0.076)	
ρ_v			0.376***		0.383***	
			(0.129)		(0.131)	
Constant		4.331***	4.157***	-1.649***	4.191***	-1.589***
		(0.538)	(0.386)	(0.210)	(0.380)	(0.205)
F statistics / Wald statistic						
Observations	Non-participants	2,209	5,689	5,689	5,689	5,689
	Participants		2,873	2,873	2,873	2,873
R-squared		0.105				
Households		1,281	1,281	1,281	1,281	1,281

Note: Robust standard errors in parenthesis; p-values reported for F and Wald statistics; *** p<0.01, ** p<0.05, and * p<0.1; outcome = crop sales in ln, selection is measured as an indicator variable with 1 meaning engages in crop sales. Regressions are controlled for regional and panel dummies.

Source: Author's calculations based on ESS data.