**DOCTORAL THESIS**


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# Essays on Responding to Climate Change, Social Protection, and Livelihood Diversification in Rural Ethiopia

A dissertation Submitted to the Graduate School of Social Sciences in partial fulfilment of the requirements for the Degree of Doctor of Philosophy (PhD) in Local Development and Global Dynamics


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**Abstract**

The nexus between the environment and development is often analysed through the sustainable livelihoods framework and within this framework, livelihood diversification has dominated much of the literature on sustainable livelihoods in the late 1990s and early 2000s (see Tacoli, 1998; De Haan, 1999; Ellis, 2005). This literature shows that agriculture is not the only source of livelihood for rural people in developing countries and diversifying into non-farm activities is increasingly adopted as a viable livelihood strategy and growing in its importance. Since then however, diversification seems to have lost favour in both the academic and policy discussions. Recently, with climate change and the recognition of its adverse impacts on livelihoods at the forefront in the developing world, there is a revival of interest and discussion on diversification as one of the main strategies by which rural people can respond to the challenges of climate change.

This thesis is an effort to document local ways of responding to the impacts of climate change and how existing policy instruments at macro and meso level mainly social protection schemes contribute to the efforts already undertaken by individual households at micro level. In view of this, the thesis contains four studies which provide theoretical and empirical analysis on non-farm diversification and the role of the Productive Safety Net Programme (PSNP) in climate change adaptation in rural Ethiopia.

The first study discusses the perceptions of smallholders' towards climate variability and change as well as local adaptation strategies based on a case study of two districts in Northern Ethiopia. The study makes use of primary data gathered from focus group discussions and in-depth interviews with farmers and secondary data on key climate variables–rainfall and temperature and compares farmers' perceptions with climate records. The results show that farmers perceive changes in their local climate and their overall perception matches with the

results from rainfall and temperature trend analysis. The study also reveals that the greatest impact of these changes in rainfall and temperature are felt on the subsistence farming, which is already hard-pressed to meet the ever-inextricable challenge of food insecurity. Smallholders are also found to employ farm-level adaptation strategies combined with diversification. However, the current level of diversification appears to be dominated by natural resource-based strategies that may not be sufficient to deal with the impacts of current climate variability and expected changes.

The second study uses the Ethiopian Rural Household Survey (ERHS) over the period 1994–2009 to analyse the factors that determine participation and returns from non-farm activities in rural Ethiopia. This study uses both the number of activities and income to measure non-farm diversification and estimates a range of micro econometric models. The results suggest that many of the variables that determine non-farm diversification belong to pull factors and are therefore a reflection of accumulation strategies. Despite this dominant pattern, however, it is likely that the poor are also diversifying into non-farm activities to earn income during agricultural off-seasons to smooth consumption.

The third study examines the impact of non-farm income diversification on income distribution and poverty using Gini–coefficient decomposition, fixed effects and probit models. These analyses reveal that non-farm income diversification has a positive impact on rural households' welfare and income distribution. This result strengthens the argument that non-farm income diversification can be a good strategy to lessen agricultural risks.

The fourth study uses a sub-sample of the ERHS for the period 2004 and 2009 to examine the impact of the Productive Safety Net Programme (PSNP) as the main social protection scheme on household non-farm income diversification as an adaptation strategy to climate change. This is an impact evaluation study that employs the Difference-in-Differences approach

combined with Propensity Score Matching for a panel of 1306 rural households. The results indicate that receiving transfers from the PSNP, on average increases income from non-farm activities and confirms the hypothesis that social protection can promote positive adaptation strategies and serve as effective means of reducing the vulnerability of smallholders to climate change induced shocks.

**Keywords:** Climate Change, Adaptation, Livelihood Diversification, Social Protection, Ethiopia

## Overview

Current scientific evidence points to significant impacts of climate change, making it one of the major challenges facing our world today. The reality of its devastating impacts on people and nations is already unfolding through increasing global temperature and associated extreme events such as sea level rise, droughts, flooding, heat waves (Intergovernmental Panel on Climate Change (IPCC), 2007; 2012; 2014). These extreme events are likely to worsen in the coming decades as most projections show that temperature continues to rise and precipitation becomes more unpredictable (see IPCC's Special Report on Managing the Risks of Extreme Events (SREX), IPCC, 2012).

Although many public debates and political discussions are currently focused on cutting back emissions in an effort to mitigate climate change, the inevitability of global warming owing to the unabated current and previous emissions (lagged effects)[1], necessitates the need for adaptation actions that can help people to reduce or increase benefits (Wreford, Moran, & Adger, 2010; Mendelsohn & Dinar, 2009).The issue of adaptation is particularly relevant for developing countries due to their high vulnerability to climate change impacts (Agrawala & Van Aalst, 2008). Thus, reducing vulnerability to climate change through adaptation measures is also increasingly considered as a prerequisite for sustainable development (Erikson & O'Brien, 2007).

The recent Fifth Assessment Report of the IPCC's Working Group II (IPCC, 2014) indicates that climate change impacts are expected to worsen the existing poverty in most developing countries. This particularly applies to many parts of rural Africa where people are already

[1] The concentration of Green House Gases (GHGs) have been rising and building-up in the atmosphere, particularly after the industrial revolution. These gases trap heat and increase global temperature through their effect primarily on warming the oceans which then leads to long-term changes in climate (Mendelsohn & Dinar, 2009). Due to the lengthy period of time it takes for the oceans to warm, a lag exists between emissions and temperature changes(Gupta, 2002).

struggling with extreme poverty and food insecurity. The IPCC reports also show that temperatures in Africa are projected to rise faster than the global average increase during this century (IPCC, 2007; 2014). Similarly, many regions in Sub Saharan Africa (SSA) are likely to experience greater variability in rainfall patterns than other areas (IPCC, 2007). These changes coupled with the low capacity to withstand the effects of climate change, already warmer climates, and heavy reliance on agriculture and natural resources (Kurukulasuriya & Mendelsohn, 2007; Hassan & Nhemachena, 2008; Thornton et al., 2010) are expected to increase the level of poverty and suffering for millions in the region.

The impact of climate change on the agricultural sector is expected to be harsh as the sector is much sensitive to weather and climate variables (Dinar, 2008; Kurukulasuriya & Mendelsohn, 2008; Seo et al., 2009). The effect of climate change on agriculture puts the issue of ensuring food security in the spotlight in SSA, especially for countries like Ethiopia that have already been affected by climate variability and for decades, experienced a series of extreme events such as drought.[2] Thus, this thesis looks into the vulnerability of Ethiopia to climate change and assess the extent to which diversification can serve as an adaptation strategy to the effects of climate change.

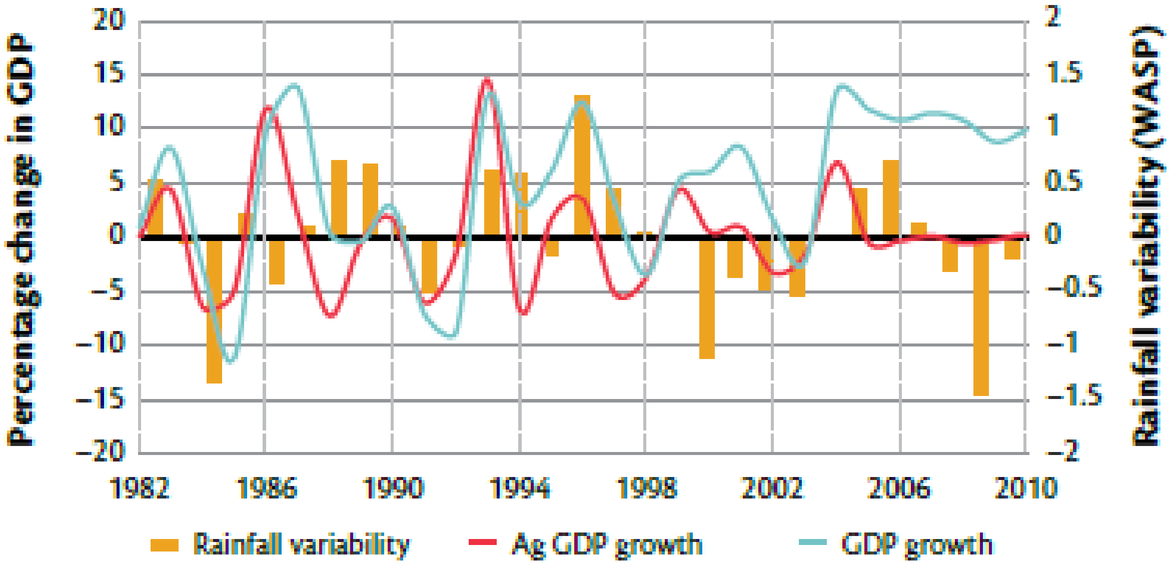
## Climate Variability and Change: The Ethiopian Context

Ethiopia is one of those countries that are extremely vulnerable to climate change. Its geographical location and topography, coupled with low adaptive capacity due to low level of development and dependence on agriculture, explain its vulnerability to the impacts of

[2] Over the past 30 years, the country has experienced several localized droughts and seven major droughts out of which, five resulted in famines (World Bank, 2010).

climate change (World Bank, 2010). Some macroeconomic indicators of the recent performance of the Ethiopian Economy are presented in **Table A** (annexed). Agriculture is the mainstay of its economy contributing 42 % of its GDP and employing close to 80% of its population (FDRE, 2011), clearly indicting the link between climate and the economy as shown in **Figure 1**. The majority of farmers are smallholders that depend on rain-fed agriculture for subsistence production, which makes them highly exposed to climate variability and consequently to both transient and chronic food insecurity (Conway & Schipper, 2011).

**Figure 1: Economic growth and rainfall variability in Ethiopia, 1982–2010**




Source: Thornton et al.(2014:3315) based on data from the World Bank (2013) and IRI/LDEO (2013).

*Note:*
The graph shows the relationship between rainfall variability and growth in GDP and agricultural GDP. Rainfall variability is measured as a percentage variation from the long-term average and expressed as the 12-month Weighted Anomaly of Standardized Precipitation (WASP).

Ethiopia has a wider range of climatic zones that vary in altitude and location. Altitudinal variation induces temperature changes and is a factor for the formation of three main climatic zones –cool (Dega), temperate (Weyna Dega), and hot (Kola). The mean annual rainfall distribution in the country ranges from a maximum of more than 2000 mm over the South-Western highlands to a minimum of less than 300 mm over the South-Eastern and North-Western lowlands. Similarly, mean annual temperature varies considerably, from lower than $15^0$C over the highlands to over $25^0$C in the lowlands. This climate variability is used to classify the three seasons in the country mainly based on rainfall regimes. These are the dry season (*Bega*) from October to January; the short rainy season (*Belg*) from February to May and the long rainy season (*Kiremet*) from June to September (FDRE, 2007; Livelihoods Integration Unit (LIU), 2011).

In Ethiopia, climate variability is common and has caused several droughts and floods, undermining food security and even causing famine for decades. Drought and floods are the major climatic hazards in Ethiopia and occur every 3 to 5 years. Since the early 1980s the country has suffered five major droughts that caused famines (Dessalegn, 1991;World Bank, 2009). Over the last two decades, the frequency and severity of droughts has increased in many parts of the country and are likely to continue with increasing trend in global warming (Williams & Funk, 2011; Shiferaw et al., 2014). These droughts have caused livelihood breakdowns, aggravated poverty and triggered major catastrophes such as the 1972/73 and 1984 *Wello* famines (Webb & Braun, 1994). Likewise, flooding caused considerable damages to lives and livelihoods by destroying crops and infrastructure in different parts of the country in 1988, 1993, 1994, 1995, 1996, and 2006 ( ICPAC, 2007 cited in World Bank, 2010).

## Observed Trends, Climate Projections and Impacts

Global warming is already happening now and previous and existing changes help to indicate possible upcoming changes. Consistent with the global and African trends, analysis of observed temperature data indicates that there has been an increase in seasonal and annual mean temperature in many areas of Ethiopia over the past five decades (Conway, Mould, & Bewket, 2004; Funk et al., 2008). For instance, the National Meteorological Agency of Ethiopia (NMA) reports that between 1951 and 2006, the annual minimum temperature increased by about 0.37°C every decade (FDRE, 2007). This trend is also confirmed by our analysis of temperature data, which has shown an increasing and statistically significant trend between 1960 and 2006 (see **Figure 2**).

Rainfall in Ethiopia shows a high inter-annual and inter-seasonal variability and since the spatial and temporal variation of precipitation is high, large-scale trends may not actually indicate regional or local circumstances (Keller, 2009). According to the National Meteorological Agency (NMA), average countrywide annual rainfall trends remained constant between 1951 and 2006 (FDRE, 2007). Despite this, however, some studies report a declining trend in the amount of rainfall in most areas of the country. For instance, Seleshi and Camberlin (2005) studied trends in extremes of seasonal rainfall over the period 1965-2002 and found that there is a decreasing trend in rainfall amount for the main rainy season between June and September (Kiremt). Other studies also indicate that growing season rainfall has decreased by 15–20 % across parts of southern, south-western, and south-eastern Ethiopia between the mid-1970s and late 2000s (FEWS NET, 2012).

The impact of climate change on Ethiopia can be explained in terms how the key climatic variables of temperature and precipitation are likely to unfold in the coming decades.

*Temperature*

According to the IPCC's 2007 Third Assessment Report (TAR), the African continent in its entirety will experience relatively higher mean temperature increases than the global mean in the last decades of this century (as compared to the same periods in the previous century). This increase in temperature is forecasted to fall in the range of $3^0$C to 4 $^0$C by using the Multi-Model Dataset (MMD)[3] with the moderate A1B scenario.[4] Similarly, using the IPCC's mid-range (A1B) emission scenario, the National Meteorological Agency (NMA) of Ethiopia indicates that the mean annual temperature is likely to increase significantly when compared to the 1961-1990 level, by a maximum of $1.1^0$C by 2030, 2.1 $^0$C by 2050 and $3.4^0$C by 2080 (FDRE, 2007) (see **Figure 3**, annexed).

*Rainfall*

The IPCC's projections indicate that there will be a 7% increase in the mean precipitation for East Africa in the last decade of this century as compared to the same period in the previous century (IPCC, 2007). In general terms, this might indicate that the Ethiopian highlands will receive a lot of rain in the future. In fact, the recent IPCC report notes that "in regions of high or complex topography such as the Ethiopian Highlands, downscaled projections indicate likely increases in rainfall and extreme rainfall by the end of the 21st century" (IPCC, 2014: 22). However, unlike the projections for temperature there is a lot of uncertainty surrounding the future pattern of rainfall. In this regard, the Ethiopian National Meteorological Agency

[3] The Multi-Model Dataset involves the use of various individual simulation models in order to arrive at more reliable projections through triangulation (IPCC, 2007).

[4] A1B is among the IPCC's four major story lines or emission scenarios that were developed to help facilitate the analysis of possible climate change and options to mitigate. The A1B scenario belongs to the A1 scenario, which describes a future world characterized by very rapid economic growth and rapid introduction of new and more efficient technologies with a world population that peaks in mid-century and declines thereafter. The A1B group emphasises on a balance across all sources of energy without dependence on any single source. With this emission scenario, global averaged surface temperature (relative to 1870-1899 baseline) is likely to increase by 2.5 °C by 2050 (IPCC, 2001; Gupta, 2002).

(NMA) reports that the average countrywide annual rainfall pattern remained constant between 1951 and 2006 and is likely to show little change in the future (FDRE, 2007). However, some studies indicate that rainfall distribution has exhibited high variability with dramatic reductions in the Belg (short) rainy season in East and South-East parts of the country after 1997 related to "anthropogenic warming in the Indian ocean" (Fung et al., 2005 cited in Regassa, Givey, & Castillo, 2010:18).

A warming temperature could result in an increase in weeds and pests, reduction in crop and livestock production, and increase the incidence of tropical diseases (mainly malaria) and loss of natural resources and ecosystems such as lakes, wetlands and loss of biodiversity (FDRE, 2007). However, more than the change in temperature, the impacts of climate change on Ethiopia will largely be determined by the distribution of precipitation over the land surface. For instance, Haakansson (2009) citing a study by Kassahun (2008) indicates how climate change can affect different geographical areas in the country mainly through its effect on rainfall distribution. Thus, the Northern, North-East and South-East parts of the country are likely to receive less rain. Given that these areas are already prone to droughts and famines means that climate change can have a devastating impact on the food security of millions of people.

A more or less similar effect but with a different scenario of increasing rainfall is also predicted to prevail in central Ethiopia (FEWS NET, 2012), which is already experiencing soil erosion and land degradation due to population pressure, deforestation and overgrazing. This is likely to aggravate the problem of erosion with more intensive rains falling within a short space of time, leading to loss of huge amount of top soil and the resultant decline in crop production in the highlands and increasing floods and water logging in the lowlands (Kassahun, 2008 cited in Haakansson, 2009).

At this juncture, it can be argued that both increases in temperature and greater variation in rainfall are most likely to increase the frequency and intensity of extreme climatic events, mainly droughts and floods which can trigger major livelihood shocks in the country. The specific impacts of the ongoing and projected climate change are summarized in Table 1

**Table 1: Impacts of Climate Change in Ethiopia**

| **Sector** | **observed and potential impacts** |
|---|---|
| Agriculture, food security | The increasing year-to-year variability and increases in both droughts and heavy precipitation events lowers agricultural production with corresponding negative effects on food security. |
| Water | The availability of clean drinking water is likely to decrease due to the increasing evaporation and the increasing variability of rainfall events. |
| Health | Incidences of malaria in areas of the highlands where malaria was previously not endemic. The warming is further expected to cause an increase in cardio-respiratory and infectious diseases. |
| Ecosystems | Climate change but also human drivers such as forest fires threaten forest ecosystems. Furthermore, a large number of plant and animal species is threatened by extinction, as climate conditions are changing too quickly for them to adapt. |
| Infrastructure | Heavy rainfall events and floods cause damages to roads and buildings. |

Source: compiled from NMA (2001) and Keller (2009).

In Ethiopia, rural livelihoods are primarily influenced by the environment since the majority of farmers and pastoralists depend on rain-fed system. Some even argue that economic factors act only as additional challenges to environmental factors (Dorosh & Rashid, 2013:23). In this regard, a study on the economic impacts of climate change on Ethiopia by Gebreegziabher et al. (2011) suggests that climate change can have severe negative impacts on Ethiopia’s agriculture.

In sum, the available evidence indicates that climate change poses a great challenge for tackling the persistent problem of food insecurity in Ethiopia. This thesis therefore argues that a more cost-effective and efficient way of adapting to climate change is one that builds on the current autonomous adaptation strategies that are pursued by smallholders. In addition, it discusses the possibilities of integrating social protection and climate change adaptation measures to enhance the resilience of people to the impacts of climate change as evidenced in the context of South Asia.

Various studies on social protection indicate that it can play a significant role in promoting productive investment in sectors such as smallholder agriculture; increase the resilience of households to shocks that can deplete their productive assets; enhance risk taking and entrepreneurial abilities of people; and help to smooth consumption (Devereux & Sabates-Wheeler, 2004; Davies et al., 2009).

Similar to adaptation measures, social protection can play a positive role in promoting livelihoods and enhancing the risk management strategies of people (Devereux & White, 2010). There is also an increasingly recognized nexus between climate change adaptation and social protection schemes as both seek to reduce the vulnerability of people to livelihood shocks (Linnerooth-Bayer, 2008; Siegel, Gatsinzi, & Kettlewell, 2011). But, empirical evidences for such an integrative approach is quite scarce in the African context perhaps as the issue came recently to the attention of researchers engaged the field of social protection.

In Ethiopia, as in the rest of the developing world, the link between social protection and climate change adaptation is not well-understood and empirically established (see Davis et al., 2013). Thus, the extent to which the existing social protection programme in Ethiopia support and/or constrain the scope for implementing adaptive responses has not been studied systematically. This thesis is therefore an attempt to fill this gap by examining to what extent the existing social protection scheme–the Productive Safety Net Programme (PSNP) promotes livelihood strategies, with a focus on diversification, by smallholders as autonomous climate change adaptation strategy. As several studies show, diversification can serve as an important strategy for adapting to climate change in rural Africa. This is because it spreads risks and act as the main form of self-insurance (Barrett, Reardon, & Webb, 2001:322). This is particularly relevant in rural Ethiopia where there is the absence of formal, market-based insurance. More importantly, however, as our findings show, diversification does not seem to be a transient phenomenon or one just associated with survival in the face of adversity such as climate related disasters but it is also "associated with success at achieving livelihood security under improving economic conditions''(Ellis, 1998:2). By focusing on diversification, this thesis also contributes to the existing theme in climate change literature namely, spatial scale (Adger et al., 2005) that attempts to shed light on the interactions between national polices and their effects on local level adaptation efforts.

## References


Adger, N., Arnell, N. W., & Tompkins, E. L. (2005). Successful adaptation to climate change across scales. *Global Environmental Change*, *15*(2), 77–86. doi:10.1016/j.gloenvcha.2004.12.005

Agrawala, S., & Van Aalst, M. (2008). Adapting development cooperation to adapt to climate change. *Climate Policy*, *8*(2), 183–193. doi:10.3763/cpol.2007.0435

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331.

Conway, D., Mould, C., & Bewket, W. (2004). Over one century of rainfall and temperature observations in Addis Ababa, Ethiopia. *International Journal of Climatology*, *24*(1), 77–91.

Conway, D., & Schipper, E. L. F. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global Environmental Change*, *21*(1), 227–237. doi:10.1016/j.gloenvcha.2010.07.013

Davies, M., Guenther, B., Leavy, J., Mitchell, T., & Tanner, T. (2009). Climate Change Adaptation, Disaster Risk Reduction and Social Protection: Complementary Roles in Agriculture and Rural Growth? *IDS Working Papers*, *2009*(320), 01–37. doi:10.1111/j.2040-0209.2009.00320_2.x

Dessalegn, R. (1991). *Famine and Survival Strategies: A Case Study of Northeast Ethiopia*. Nordic Africa Institute.

Devereux, S., & Sabates-Wheeler, R. (2004). *Transformative Social Protection* (No. IDS Working Paper 232). Institute of Development Studies, Brighton, Sussex.

Devereux, S., & White, P. (2010). Social Protection in Africa: Evidence, Politics and Rights. *Poverty & Public Policy*, *2*(3), 53–77. doi:10.2202/1944-2858.1078

Dinar, A.(2008). *Climate Change and Agriculture in Africa: Impact Assessment and Adaptation Strategies*. Earth scan.

Dorosh, P., & Rashid, S. (2013). *Food and Agriculture in Ethiopia: Progress and Policy Challenges* (Vol. 74). University of Pennsylvania Press.

Ellis, F. (1998). Household strategies and rural livelihood diversification. *Journal of Development Studies*, *35*(1), 1–38. doi:10.1080/00220389808422553

Environment for Development (EfD) (2012). *Ethiopia 2011/2012* (EfD Initiative Centre). Addis Ababa: Environmental Economics Policy Forum for Ethiopia (EEPFE).

Eriksen, S., & O’Brien, K. (2007). Vulnerability, poverty and the need for sustainable adaptation measures. *Climate Policy*, *7*(4), 337–352.

Federal Democratic Republic of Ethiopia (FDRE) (2007). *Climate Change Adaptation Programme of Action (NAPA) of Ethiopia*. Addis Ababa: Ministry of Water Resources and National Meteorological Agency.

FDRE (2011). Ethiopia’s Climate-Resilient Green Economy: Green Economy Strategy. Addis Ababa.

FDRE (2014) *Growth and Transformation Plan Annual Progress Report for F.Y. 2012/13*. Addis Ababa: Ministry of Finance and Economic Development.

Famine Early Warning Systems Network (FEWS NET) (2012). *A Climate Trend Analysis of Ethiopia*. Famine Early Warning Systems Network-Informing Climate Change Adaptation Series. Retrieved from http://pubs.usgs.gov/fs/2012/3053/FS12-3053_ethiopia.pdf

Gebreegziabher, Z., Stage, J., Mekonnen, A., & Alemu, A. (2011). Climate change and the Ethiopian economy: A computable general equilibrium analysis.

Gupta, J. (2002). *Our Simmering Planet: What to Do About Global Warming?*. Zed Books.

Haakansson, M. (2009). *When the Rains Fail: Ethiopia’s Struggle Against Climate Change*. Informations Forlag.

Hassan, R., & Nhemachena, C. (2008). Determinants of African farmers’ strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, *2*(1), 83–104.

Intergovernmental Panel on Climate Change (IPCC) (2007) *Climate Change 2007 - Impacts, Adaptation and Vulnerability: Working Group II contribution to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)*. Cambridge University Press.

IPCC (2012). *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (Special Report) (p. 582). Cambridge University Press, Cambridge, UK and New York, NY, USA: Inter-governmental Panel on Climate Change.

IPCC (2014). Climate change 2014: impacts, adaptation, and vulnerability. *Working Group II Contribution to the IPCC 5th Assessment Report-Technical Summary*, 1–76.

Keller, M. (2009). *Climate Risks and Development Projects Assessment Report for a Community-Level Project in Guduru, Oromiya, Ethiopia* (Assessement Report). BFA

( Bread For All). Retrieved from http://www.iisd.org/cristaltool/documents/BFA-Ethiopia-Assessment-Report-Eng.pdf

Kurukulasuriya, P., & Mendelsohn, R. (2007). *Crop Selection : Adapting To Climage Change In Africa*. The World Bank. Retrieved from http://dx.doi.org/10.1596/1813-9450-4307

Kurukulasuriya, P., & Mendelsohn, R. O. (2008). How will climate change shift agro-ecological zones and impact African agriculture? *World Bank Policy Research Working Paper Series, Vol*.

Linnerooth-Bayer, J. (2008). International social protection for climate-related disasters. *The Irrational Economist*.

Livelihoods Integration Unit (LIU) (2011). An Atlas of Ethiopian Livelihoods. Disaster Risk Management and Food Security Sector, Ministry of Agriculture and Rural Development (MORAD). Retrieved from http://www.fegconsulting.com/spotlight/complete atlas/Atlas Final Print Version June 2029 202011.pdf

McSweeney, C., New, M., & Lizcano, G. (2010). *UNDP Climate Change Country Profiles: Ethiopia*. Retrieved from http://country-profiles.geog.ox.ac.uk

Mendelsohn, R. O., & Dinar, A. (2009). *Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional Effects*. Edward Elgar Publishing.

Regassa, S., Givey, C., & Castillo, G. (2010). The Rain Doesn't Come On Time Anymore: Poverty, vulnerability, and climate variability in Ethiopia. *Oxfam Policy and Practice: Climate Change and Resilience*, *6*(1), 90–134.

Río, S. del, Herrero, L., Fraile, R., & Penas, A. (2011). Spatial distribution of recent rainfall trends in Spain (1961–2006). *International Journal of Climatology*, *31*(5), 656–667.

Seo, S. N., Mendelsohn, R., Dinar, A., Hassan, R., & Kurukulasuriya, P. (2009). A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa. *Environmental and Resource Economics*, *43*(3), 313–332.

Shiferaw, B., Tesfaye, K., Kassie, M., Abate, T., Prasanna, B., & Menkir, A. (2014). Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and Climate Extremes*.

Siegel, P. B., Gatsinzi, J., & Kettlewell, A. (2011). Adaptive Social Protection in Rwanda:"Climate-proofing"the Vision 2020 Umurenge Programme. *IDS Bulletin*, *42*(6), 71–78.

Thornton, P. K., Ericksen, P. J., Herrero, M., & Challinor, A. J. (2014). Climate variability and vulnerability to climate change: a review. *Global Change Biology*, *20*(11), 3313–3328.

Thornton, P. K., Jones, P. G., Alagarswamy, G., Andresen, J., & Herrero, M. (2010). Adapting to climate change: Agricultural system and household impacts in East Africa. *Agricultural Systems*, *103*(2), 73–82. doi:10.1016/j.agsy.2009.09.003

United Nations Development Programme (UNDP) (2014). *Ethiopia: Country Economic Brief 2014*. United Nations Development Programme, Ethiopia Country Office.

Williams, A. P., & Funk, C. (2011). A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. *Climate Dynamics*, *37*(11-12), 2417–2435.

World Bank. (2009). *Ethiopia: Diversifying the Rural Economy. An Assessment of the Investment Climate for Small and Informal Enterprises* (MPRA Paper). Retrieved from http://mpra.ub.uni-muenchen.de/23278/

World Bank. (2010). *Economies of Adaptation to Climate Change: Ethiopia*. Washington, DC. Retrieved from http://climatechange.worldbank.org/sites/default/files/documents/EACC_Ethiopia.pdf

Wreford, A., Moran, D., & Adger, N. (2010). *Climate change and Agriculture*. OECD.

Yue, S., & Hashino, M. (2003). Temperature trends in Japan: 1900–1996. *Theoretical and Applied Climatology*, *75*(1-2), 15–27.

## Annex

**Table A: Summary of selected indicators of macroeconomic and main sectors performance in Ethiopia (2006–2013)**

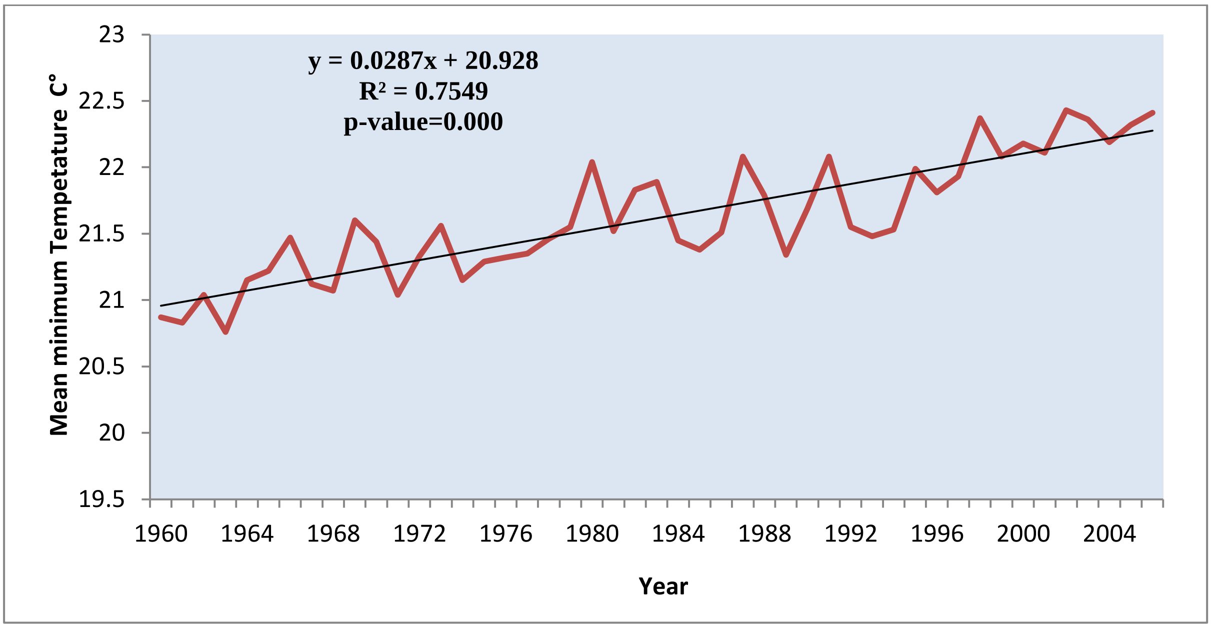
| Indicators | 2006/07 | 2007/08 | 2008/09 | 2009/10 | 2010/11 | 2011/12 | 2012/13 |
|---|---|---|---|---|---|---|---|
| Real GDP Growth rate | 11.8 | 11.2 | 10.0 | 10.4 | 11.4 | 8.8 | 9.7 |
| Sub-Saharan average | 6.7 | 5.5 | 2.8 | 5.3 | 5.2 | 4.9 | 5.0 |
| Agriculture (%) | 9.4 | 7.5 | 6.4 | 7.6 | 9.0 | 4.9* | 7.1 |
| Industry (%) | 9.5 | 10.1 | 9.7 | 10.6 | 15.0 | 17.1 | 18.5 |
| Services (%) | 15.3 | 16.0 | 14.0 | 13.0 | 12.5 | 10.6 | 9.9 |
| GDP per capita US$ | 270 | 359 | 419 | 377 | 389 | 510 | 550 |
| Inflation (year average) | 15.1 | 55.3 | 2.7 | 7.3 | 38.1 | 20.5 | 7.4 |
| Exchange rate (year average) | 8.68 | 9.24 | 10.42 | 12.89 | 16.1 | 17.5 | 18.3 |
| Gross reserve (in month of import) | 2.1 | 1.2 | 1.8 | 2.1 | 3.1 | 2.0 | 1.9 |
| External debt (% of GDP) | 11.8 | 10.4 | 13.5 | 18.1 | 22.0 | 21.5 | 24.3 |
| Mid-year Population in millions | 72.4 | 74.9 | 76.8 | 78.8 | 80.9 | 83.0 | 84.8 |

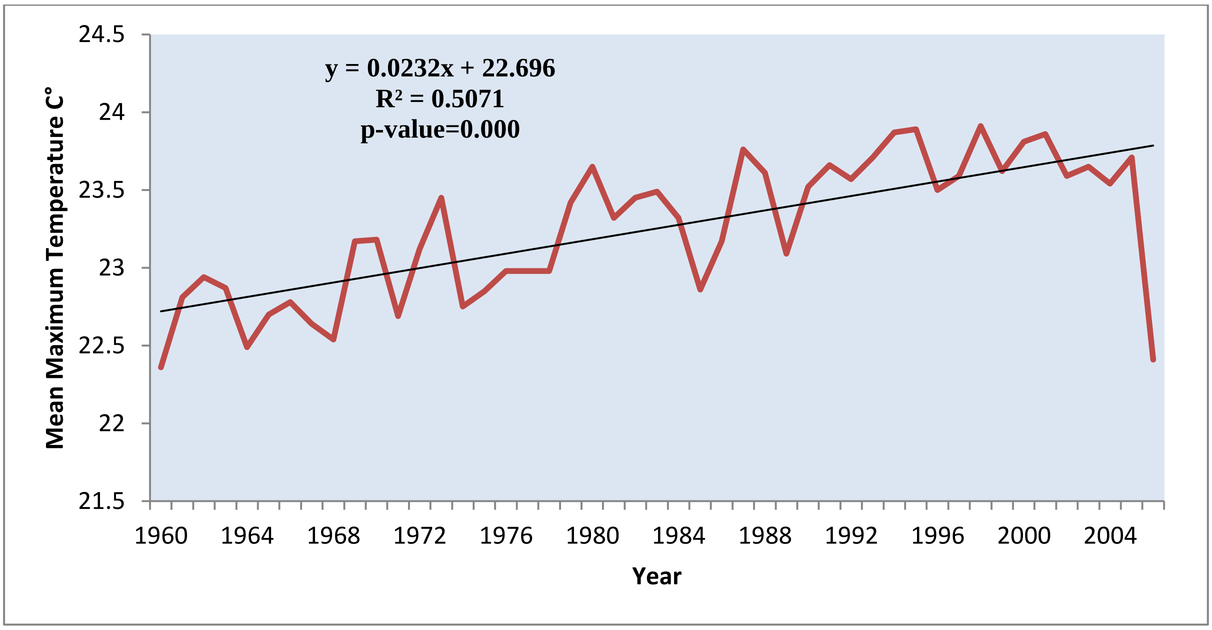
Source: UNDP (2014) based on Ministry of Finance and Economic Development (MoFED) (National Accounts).

*Note:* Ethiopian Fiscal year runs from July 8 to July 7

* The reduction of the growth share of agriculture's value added from 9.0 in 2010/11 to 4.9 % in 2011/12 may be explained by the reduction of crop production in 2011/12. Thus, the Growth and Transformation Plan's annual progress report (2012/13) indicates that productivity for major crops declined from 7.67 (quintal/hectare) in 2010/11 to 5.82 (quintal/hectare) in 2011/12 for the *Belg* season. Moreover, data for oil seed production for smallholder farmers for the same season is not reported for the year 2011/12 (FDRE, 2014: 33). Crop production being the major subsector of the agricultural sector that accounts for over 30 % of the total gross domestic product, its reduction can significantly affect overall agricultural GDP. The reduction in crop production can also be attributed to shortage of rainfall in areas that depend on *Belg* production following the major drought in the Horn of Africa in 2011 that affected more than 12 million people across Ethiopia, Somalia, and Kenya (Environment for Development (EfD), 2012).

**Figure 2: Observed Minimum and Maximum Temperature over Ethiopia (1960–2006)**



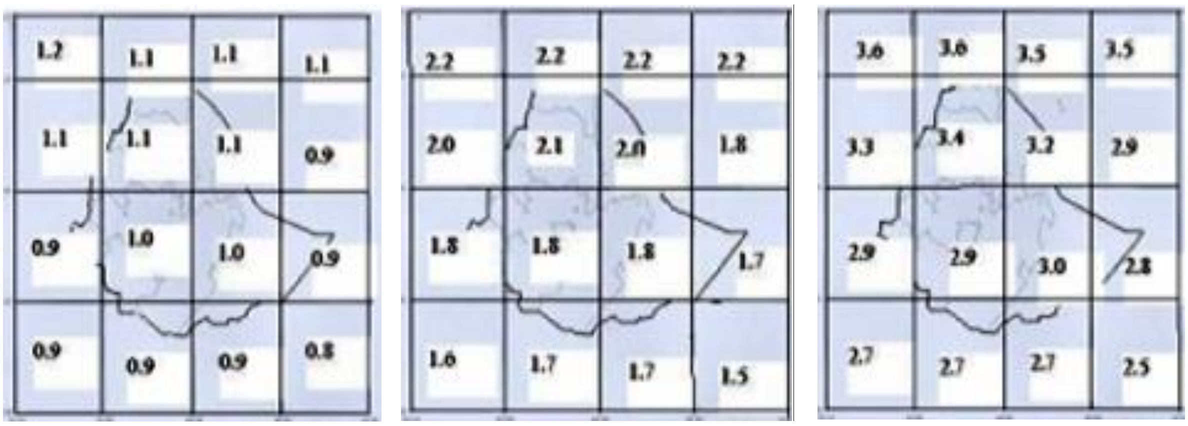




Source: Computed from UNDP's Climate Change Country Profiles dataset compiled by McSweeney, New, & Lizcano (2010).

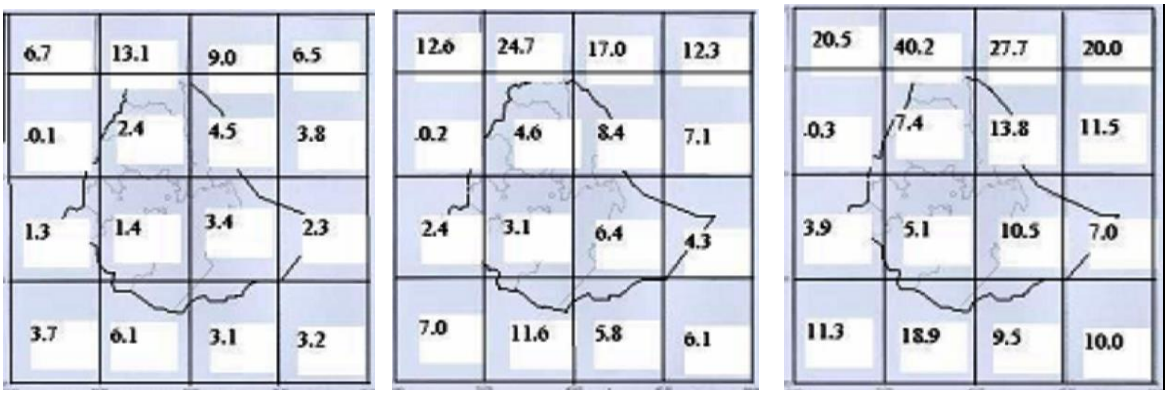
*Notes*:

The minimum and maximum temperature data were used to determine the presence of trends in their time series and simple linear regression is used to see if these trends have statistical significance based on t-test. Following similar studies by Yue & Hashino (2003) and Río et al. (2011), we have also applied non-parametric Mann-Kendall (M-K) test to assess monotonic trend and its significance (these methods are further discussed in the first paper). Both the linear regression and M-K assume a linear trend in the time series and show that there is significant and positive trend for both minimum and maximum temperature during the period 1960-2006 in Ethiopia.

**Figure 3: Composite (average of 19 GCMs) change in temperature (C°) and rainfall relative to 1961-1990 normal for A1B emission scenario.**




**Change in temperature -2030** **Change in temperature -2050** **Change in temperature -2080**




**change in rainfall (%)-2030** **change in rainfall (%) -2050** **change in rainfall (%)-2080**

Source: Federal Democratic Republic of Ethiopia (FDRE), Ministry of Water Resources and National Meteorological Agency (FDRE, 2007).

*Notes:*

According to the NMA, these climate projections generated using two soft wares– MAGICC (Model for the Assessment of Greenhouse-gas Induced Climate Change) and SCENGEN (Regional and global Climate SCENario GENerator) for the three periods–2030, 2050 and 2080.

MAGICC gives projections of global-mean temperature and sea level change due to melting ice and thermal expansion of water in global reservoirs. SCENGEN provides projections of future climate change on 5° latitude by 5° longitude grid.

The projection results are for a mid-range emission scenario and it is likely that lowest and highest emission scenarios may result in different changes in these climate variables.

The annual precipitation is expected to slightly increase over the country while temperature is likely to show a marked increase particularly in the North West part of the country (the Amhara region).

## Essay 1

# Perceptions of and Adaptation to Climate Variability and Change: A Case Study of Smallholder Farmers in Northern Ethiopia


### Abstract

Based on qualitative data obtained through Key Informant Interviews, Focus Group Discussions, and Participatory Rural Appraisal techniques, as well as secondary data on rainfall and temperature records, this paper examines the perceptions of and adaptation strategies to climate variability and change in two districts in Northern Ethiopia. It specifically seeks to examine to what extent smallholder agriculturalists use livelihood diversification strategies away from climate-dependent farm and natural resource-based activities to offset the impacts of climate-induced shocks. The results show that farmers perceive changes in their local climate and are able to identify context-specific indicators that broadly corroborate the results from rainfall and temperature trend analysis. Concerning adaptation strategies, smallholders employ farm-level adaptation to climate variability and change that mostly involve soil and water conservation structures. Diversification is also an integral part of autonomous adaptation strategies in the two districts. However, current patterns of diversification appear to be dominated by natural resource-based activities that may not be sufficient to deal with the impacts of current climate variability and expected changes. This highlights the need to adopt vigorous policy interventions geared towards increasing investments in rural and agricultural development to support the ability of smallholders to engage in beneficial forms of non-farm diversification strategies.



Key words– Smallholders, Climate variability, Autonomous Adaptation, diversification, Ethiopia

## 1. Introduction

In its latest report, the Intergovernmental Panel on Climate Change Climate (IPCC) states that anthropogenic Green House Gas (GHC) emission particularly from the energy and industry sectors, is growing at an increasing pace (IPCC, 2014). This unabated emission is expediting global warming trend and the change in climate. The IPCC's previous report also establishes that less developed regions are at the receiving end of the adverse impacts of climate change (IPCC, 2007).

Sub-Saharan Africa is one such region that is extremely vulnerable to climate change with most climate projections indicating that the region could experience a relatively higher increase in mean temperatures and greater variability in rainfall patterns than other regions in the coming decades (IPCC, 2007). African smallholders are the most at risk from the impacts of climate variability and change since they depend on rain fed agriculture (IPCC, 2007; Conway & Schipper, 2011). According to the IPCC, rain fed crop production is likely to decline by 10–20% by 2050 and crop revenues could fall by up to 90 % by the end of this century (IPCC, 2007). This, against the backdrop of increasing population pressure and dwindling natural resources, indicates the magnitude of the problem and the need to put in place adaptation measures to prevent a catastrophic events.

Ethiopia is one of the sub-Saharan African countries that are extremely vulnerable to climate change. According to Climate Change Vulnerability Index, the country is in the 'extreme risk' category and ranks 7$^{th}$ in the list of countries most at risk from climate change in 2015 (Maplecroft, 2015).[5]

[5] Maplecroft identifies 32 'extreme risk' countries in its latest Climate Change Vulnerability Index (CCVI). This index is calculated by assessing the sensitivity, the physical exposure, and the governmental capacity of populations and countries to adapt to climate change over the next 30 years. These countries are mainly characterized by heavy reliance on agriculture with 65% of their combined working population employed in the sector, while 28% of their overall economic output relies on agricultural revenues. Moreover, the index factors

Agriculture is the mainstay of Ethiopia's economy contributing around 42% of its GDP and employing 80% of its population (FDRE, 2011), clearly indicting the high dependence on agriculture. The majority of farmers are smallholders that depend on rain-fed agriculture for subsistence production making them highly vulnerable to climate variability and extremes (Conway & Shipper, 2011).

Most climate models predict that temperatures in Ethiopia will increase over the coming years reaching up to 2.1°C by 2050, and 3.4 °C by 2080 (FDRE, 2007). Over the past five decades, rainfall has shown high variability (FDRE, 2007),which is expected to continue to increase the frequency and severity of climatic hazards mainly droughts and floods (Deressa et al., 2011). Thus, proactive adaptation strategies are needed to reduce the impact of climate change on agriculture and to improve the resilience of smallholder farmers. In this regard, smallholders' perception of current climate variability and their response through local adaptation measures can serve as useful input to design integrated and sustainable adaptation strategies. Moreover, the following arguments can be advanced for the need to study smallholders' perception and adaptation strategies. First, past experience in agricultural technologies and natural resource management practices show, smallholders are likely to adapt new practices and adaptive strategies when the new practices are close enough to the existing practices and fit their social and environmental context (Rockstrom, 2000; Perret & Stevens, 2006; Below, Artner, Siebert, & Sieber, 2010; Kassie et al., 2013). Second, adaptation to short-term climate variability and extreme events can serve as the basis for reducing vulnerability to longer-term climate change (Lim et al., 2005:10; Baas & Ramasamy, 2008).

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in the changing weather patterns, and how these are already impacting food production, poverty, migration and social stability in these countries.

This paper contributes to the debates about autonomous adaptation by presenting an empirical study from two districts in Northern Ethiopia that are highly affected by climate variability and change. Accordingly, the following research questions are posed:

- How do smallholders perceive climate variability and change in their locality?
- What are the effects of climate variability and change? And how do smallholders experience these effects?
- How do smallholders respond to climate variability and change? And to what extent does diversification prevail as an adaptation strategy?

The paper argues that assessing smallholders' perceptions of climate variability and change and existing adaptation strategies such as diversification, is a good step to understanding what works best in terms of successful adaptation to climate change at different levels and what improves the existing strategies. This is important, as perception of changes "precedes measures to adapt to climate change effects" (Swai, Mbwambo, & Magayane, 2012:218) and perception of changes in climate and environment is one component that determines the success of adaptation strategies (Kemausuor et al., 2011). Thus, understanding farmers' perceptions of current climate variability and change and their adaptation practices can be an essential input for adaptation policy since their strategies are mostly the result of long-term experiences and assessment of risks in their day-to-day production and consumption decisions (Dinar, 2008). This in turn helps to link successful bottom-up approaches with top-down strategies thereby ensuring the sustainability of adaptation measures.

The rest of the paper proceeds as follows. Section 2 provides a brief overview of general issues and background from the literature. Section 3 presents a conceptual and theoretical discussion on adaptation strategies. Section 4 gives a description of the study sites and methods. In Section 5, the results and discussion are presented. Section 6 concludes.

## 2. Climate Change and Adaptation Strategies: An overview

There is a growing awareness and increasing evidence that climate change poses a threat to achieving development and poverty reduction goals in poor countries (Agrawala & Van Aalst, 2008; Prowse et al., 2009). The risks associated with climate change can be reduced through mitigation and adaptation actions (Swart & Raes, 2007).

Mitigation involves interventions aimed at reducing or stabilizing greenhouse gas concentrations in the atmosphere so as to reduce global warming and its consequences (IPCC, 2001). Reducing greenhouse gases through mitigation takes a long time (Swart & Raes, 2007) and governments are currently slow and unresponsive in implementing mitigation agreements such as the Kyoto protocol (Gupta, 2002). Thus, many scholars argue that adaptation measures that aim to reduce vulnerability to climate change are the necessary responses to climate change in poor countries (Pielke et al., 2007; Ayers & Forsyth, 2009). Reducing vulnerability to climate change through adaptation measures is increasingly considered as a prerequisite for sustainable development (Erikson & O'Brien, 2007).

Adaptation strategies are responses to actual or expected climatic conditions that are intended to either moderate harm or exploit opportunities (IPCC, 2007).These responses can involve adjustments made in reaction to current occurrences (climate variability) or can be adaptations to long-term changes (IPCC, 2001; Swart & Raes, 2007). Moreover, adaptation can involve a number of practices by multiple actors at various levels ranging from households to institutionalized settings (Prowse and Scott, 2008). Mostly, adaptation practices that occur at household level triggered by changes in natural systems or welfare changes in human systems are referred to as autonomous adaptations. Others that are the result of a deliberate policy decisions based on knowledge of the possible change of climatic conditions are categorized into planned or institutional adaptations (Malik et al., 2010).

The theoretical literature on adaptation focuses on the different adaptation strategies and their relative efficiency. The literature identifies two broad categories: private and public adaptations, which roughly correspond to autonomous and planned adaptations. Private adaptation often involves only one beneficiary and tends to be efficient as compared to public adaptation where several beneficiaries are simultaneously involved, which increases the cost of coordination in resource allocation (Mendelsohn & Dinar, 2009). **Table 1** shows examples of actions relating to the two adaptation types.

**Table 1: Private and Public Adaptation to Climate Change in the Agricultural Sector**

| Type | Action |
|---|---|
| **Private ( autonomous)** | Changing crop species and varieties |
| | Changing livestock breed and species |
| | Changing timing of planting and harvesting |
| | Multiple cropping seasons |
| | Use of irrigation |
| | Changing land use |
| | Changing land used for livestock and herds |
| **Public (planned or institutional )** | Plant and animal breeding |
| | Public education trough extension |
| | Building dams and canals |

Source: Mendelsohn and Dinar (2009:66).

The adaptation literature also differentiates between proactive and reactive adaptations. Proactive adaptations are often undertaken in anticipation of future climate change and involve long-lasting investments in large-scale infrastructure such as dams or irrigation canals while reactive adaptations happen after the change occurs (ex-post). Given the difficulty of predicting climate change at a local level, most adaptations are expected to be reactive (Mendelsohn & Dinar, 2009). Some even argue that the best way to prepare for climate change is to adapt to current climate variability ( Smit et al., 1996; Leary et al., 2006). Here, the argument is that adaptation has to do with building up capacity (stock) that prepares the system to respond to anticipated changes in the climate system. A good example is farmers already choosing crops and livestock that are well productive in hot and dry climatic conditions, indicating that it is not necessary to wait for an abrupt change to occur and adaptation can begin now.

Much research on climate change focused on impacts on a given region or country, with less effort directed at the responses of local communities and individual households. Adaptation, however, generally takes place at micro level where farmers introduce practices at the local level influenced by factors such as seasonal climatic variations, the agricultural production system, and other socioeconomic factors (Selvaraju, Subbiah, Baas, & Juergens, 2006).

Most of the economic literature favours planned adaptation and considers the merits of autonomous adaptation somehow contentious. Forsyth and Evans (2013) summarize the debates on autonomous adaptation. Accordingly, economists seem to argue that autonomous adaptation is inefficient, and may divert resources from planned interventions (Stern, 2007; Eisenack, 2009; Chambwera & Stage, 2010:9).

On the other hand, environmental researchers argue that people for many years, have experienced environmental challenges and developed effective adaptation strategies based on their needs and livelihood strategies. These strategies are often based on indigenous knowledge and the identification of best practices and their incorporation into adaptation policies and analyses help to develop cost-effective, participatory and sustainable adaptation strategies (Chevallier, 2010). Moreover, “supporting and improving existing local adaptation strategies is more effective, less expensive and less demanding on institutional capabilities than large scale and centrally planned adaptation programmes” (Douma & Hirsch, 2007:22). These debates trigger the need for evidences on how autonomous adaptation works and links with planned adaptation (IPCC, 2012). Thus, studies have identified several practices as autonomous adaptation strategies at a household level (Smit & Skinner, 2002; Paavola, 2008). For example, Below et al. (2010) identify diversification and associated changes in livelihood strategies as the most common adaptation options pursued by agricultural households in Africa. Erikson et al. (2008) also examine adaptation strategies to climate impacts in eastern and southern Africa and find most activities to relate to diversification. Similarly, Oxfam (2008) reports diversification of animal mix as one adaptation method used by pastoralists in Eastern Africa.

Most recently, Cannon (2014:55) argues that there is a need to take a shift from dependence on climate sensitive livelihoods such as farming, fishing or pastoralism into ‘alternative rural livelihoods’ since without this shift, climate change adaptation would remain an arduous task. A further argument of Cannon is that most ideas for rural adaptation to climate change are too focused on farming, such as developing drought-resistant varieties with “little scope for preparedness for new crop pests and diseases” that could result from the changing climate. Thus, the high dependence on climate sensitive livelihoods and the uncertainty of how the change in climate is likely to unfold at a local level makes investigating the role of livelihood diversification in climate adaptation all the more important. Against this backdrop, this paper presents evidence from a qualitative case study from Northern Ethiopia.

## 3. Issues and Review of Literature

Successful adaptation to climate change involves two steps– perception of the changes in climate and taking action in response to the perceived change through adaptation strategies (Maddison, 2007). However, most studies on adaptation mainly focused on the determinants of adaptation actions using models that combine climatic, biophysical and economic variables (McCarthy et al., 2001). While such studies are important to enhance existing adaptation actions, understanding the perceptions of people who often directly experience changes in weather patterns and are affected by climate variability, is equally relevant. This is because perception is imperative in shaping the ways in which people respond to the perceived variability and change in their local climate. In this regard, Adger et al. (2009) argue that perception is one factor that plays a role either in constraining or facilitating decision-making both for individual and collective actions pertaining to adaptation. They further note "Perceptions of risk, knowledge and experience are important factors at the individual and societal level in determining whether and how adaptation takes place" (Adeger et al, 2009: 346). This section therefore reviews two groups of studies namely (1) studies that examined climate change perceptions and (2) studies that focused on local adaptation strategies.

### *Perception of Climate Variability and Change*

It is clear that people experience changes in local weather patterns. This may not necessarily reflect long-term local and global trends in climate. Nevertheless, drawing from behavioural research, many have argued that climate-change experience and its perception play an important role in adaptation and mitigation behaviour as well as in supporting policy actions (O'Connor, Bord, & Fisher, 1999; Weber, 2006; Howe, et al., 2013). The reason for this observation is that people who perceive or experience change in the climate system are “likely to take an action to reduce a risk that they encounter and worry about” and “personal evidence of global warming and its potentially devastating consequences can be counted on to be an extremely effective teacher and motivator.”(Weber, 2006:116).

Research from psychology and environmental psychology conducted in the developed world also reveal the importance of perception for climate change related actions. For instance, Joireman et al. (2010) based on three studies in the United States and Li, Johnson and Zaval, (2011) based on two studies in the United States and Australia find that individuals’ perception of increased daily temperature is likely to relate to a greater belief in and concern with global warming and positively affects the propensity to take action.

Another study by Howe et al. (2013) based on a survey from 89 countries in Africa, Asia, Europe, South and North America finds that most people perceive and adapt to local climate change and their perception largely correspond with patterns of observed temperature change from meteorological records.

Maddison (2007) based on a large-scale survey from 10 African countries ( including Ethiopia) and applying Heckman’s sample selection model on 9500 farmers analysed the two-stage process of perception and adaptation to climate change. The results show that most farmers perceive increase in temperature and decrease in rainfall and implement some adaptation measures albeit facing institutional barriers to adaptation.

Studies that focused on people’s perceptions on climate change are few in Ethiopia. Meze-Hausken (2004) based on qualitative data from group and in-depth interviews studied the perceptions of local farmers and pastoralists on rainfall conditions in Northern Ethiopia. The findings indicate that farmers strongly perceive a change in climate with a reduction in rainfall that contrasts with the climate records. The study only focused on rainfall and attributed the differences between peoples' perception and recorded rainfall data to the increase of farmers' "need for rainfall" and possible errors in rainfall data recording.

Another study by Deressa et al. (2011) looked into the perceptions of adaptation to climate change using the Heckman selection model on a sample of 1,000 households in five regions in Ethiopia. They find that farmers' perceptions are related to age, wealth, and information on climate change, social capital and agro ecological settings.

A more recent study by Kassie et al. (2013) examined farmers' perception in Central Rift and Kobo valley areas based on a household survey of 200 farmers. They used qualitative data gathered through key informant interviews and FGDs. Their findings show that farmers in both areas perceive a change in their local climate and implement various adaptation strategies that are mostly related to changing farming practices.

***Local Adaptation to Climate Change***

There are some evidences that many rural and indigenous communities are actively putting into place initiatives to adapt to climate change (see, Cooper et al., 2008; Forsyth & Evans, 2013; Campos, Velázquez, & McCall, 2014). These adaptations, particularly in smallholder agriculture, are often discussed in terms of changes in farming practices such as switching crop varieties and livestock species (Seo & Mendelsohn, 2007); irrigation, crop diversification, mixed crop and livestock farming and changing planting dates (Mertz et al., 2009; Yadav et al., 2011; Gebrehiwot & Veen, 2013).

Much of the empirical literature in Africa focuses on agricultural technology adoption in the context of climate change adaptation. Although, the importance of such adaptation measures is undeniable, it is arguable to what extent such technologies are available to majority of smallholder farmers in Africa. More importantly, however, smallholder agriculture is highly sensitive to climate conditions (Seo & Mendelsohn, 2007) and it is difficult to exactly know the change in the climate (e.g. local rainfall changes) to which farmers have to adapt, since climatic models do not predict locally-specific (scaled-down) changes (Cannon, 2014). In addition, it is possible that climate change could result in different combinations of temperature and precipitation, which in turn may add-up to the uncertainties and vulnerabilities in the smallholder agriculture such as new crop pests and plant and animal diseases. Thus, a question remains to what extent agricultural adaptations constitute a successful adaptation to climate change.

Studies on climate change adaptation therefore need to take into account various pathways to adapting that can reduce direct dependence on the climate. One of the recurrent strategies is diversifying livelihoods, which in African context, is often viewed as "an adaptation and coping strategy in response to local climate variability, recurrent shocks and climate change (D'haen, Nielsen, & Lambin, 2014:1).

There are several examples of on-farm, and non-farm diversification strategies being used to adapt to the growing threat from climate change in Africa. For instance, a study of local autonomous adaptations indicate that subsistence and cash crop diversification (on farm) are adaptations already being undertaken autonomously in many parts of southern Africa (Bauer & Scholz, 2010). Similarly, diversification into small livestock production is offering increased food security under adverse climate conditions and acting as a useful buffer to drought shocks, in countries such as Malawi (Stringer, Mkwambisi, Dougill, & Dyer, 2010:152). A further study by Roncoli et al. (2010:2) on adaptation to climate change for smallholder agriculture in Kenya report that " consistent with most findings from adaptive-strategies research in Africa, participants frequently mentioned livelihood diversification as a key adaptation strategy".

Previous studies on climate change in Ethiopia have focused on measuring the impact of climate change on agriculture (see Hailemariam, 1999; Deressa, 2007). These studies have analysed the monetary impacts of climate change using Ricardian and agronomic models and suggested some adaptation measures mainly water harvesting and irrigation. However, the studies are limited in terms of offering insights into adaptation strategies at micro or farm household level due to their aggregate nature (Falco et al., 2011). The number of studies that investigated perceptions and local adaptation strategies are limited ( Gebrehiwot & Veen, 2013; Kassie et al., 2013; Legesse, Ayele, & Bewket, 2013).

Gebrehiwot and Venn (2013) studied farm level adaptations to climate change in Tigray region, northern Ethiopia. Using a multinomial logit model and data from 400 smallholder farmers, they find similar factors influencing farmers' perceptions as reported in Deressa et al (2011).

Legesse et al. (2013) using a survey of 160 households from Doba district in Eastern Ethiopia, examined farmers' perceptions and applied a multinomial logit model (MNL) to identify factors influencing adaptation strategies of farmers to climate variability and change. They find crop diversification, soil and water conservation practices, integrated crop and livestock diversification, off-farm income activities and rainwater harvesting as the dominant adaptation strategies.

# 4. Methodology

## 4.1. Description of the Study Sites

The study was conducted in Lasta and Beyeda districts of Amhara National Regional State (ANRS) in Northern Ethiopia. The region is selected for this study as it has been frequently affected by climate variability and is likely to experience relatively higher temperature in the coming decades than other regions (see Figure 3 on page 18). The two districts belong to three major livelihood zones in the region. Lasta mainly comprises of North East Woyna-dega (moderate) Mixed Cereal (NMC) and Beyeda mostly covers the North Highland Wheat, Barley and Sheep (NWB) livelihood zone. These zones are characterized by varied climate, topography and livelihood profiles. These agro ecological and livelihood characteristics are taken into account in selecting the two districts. In addition, the following specific selection criteria are used in the purposive sampling.

1. Livelihood and vulnerability profiles

The two districts are classified as food insecure and are served by the Productive Safety Net Programme (PSNP). Thus, 40 % of Lasta and 36 % of Beyeda populations are labelled to be chronically food insecure based on the region's 2009 Food Security Coordination office figures (**Table 2**).

Beyeda district faces food deficit every year. Other than farming, migrant labour, firewood collection and local labour (an off-farm activity) are important livelihood activities. Almost all farmers depend on food purchase. The very poor depend on temporary agricultural wage labour for their income. Moreover, food aid makes an important contribution to food consumption for most households in the district.

Lasta district is also classified as chronically food insecure. The area is characterized by mixed farming (crop production and livestock). Local agricultural labour, urban and migratory labour are important sources of income for the poorer wealth groups. Shoat (sheep and goat) and cattle sales are the main source of cash income for the relatively better-off households (see **Table D** annexed for wealth ranking).

2. Presence of climatic variability and shocks

One of the objectives of the study is to assess autonomous adaptation to climate change, and it is important to consider varied climatic conditions as well as the presence of climatic shocks such as floods and droughts in order to understand the strategies people have devised based on their experiences in the past.

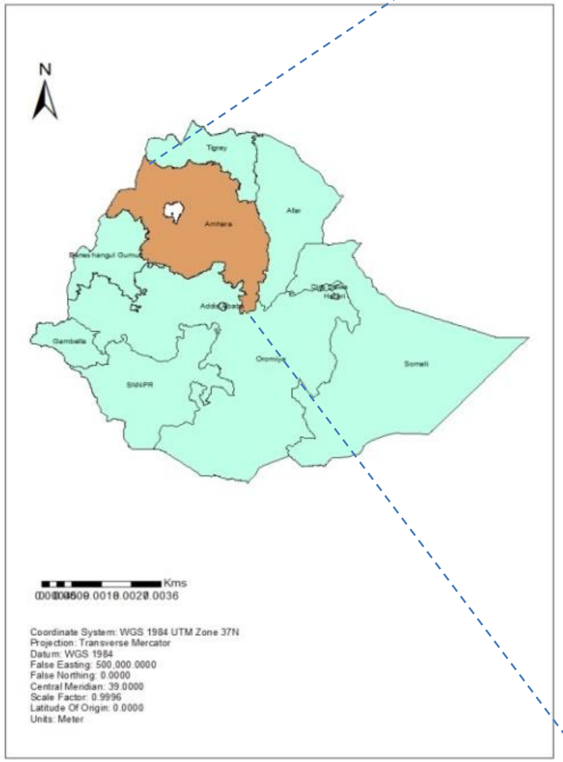
Thus, Lasta is one of the districts severely hit by frequent droughts and has been the epicentre of famine in the mid 1980's. Similarly, Beyeda is located at the foothills of the highest mountain ranges in Ethiopia – the Semien Mountains. The district's climate ranges from *werich* (very cold) to *weyna dega* (moderate) making it relatively easy to gain insight into any warming trends due to climatic variability and change.

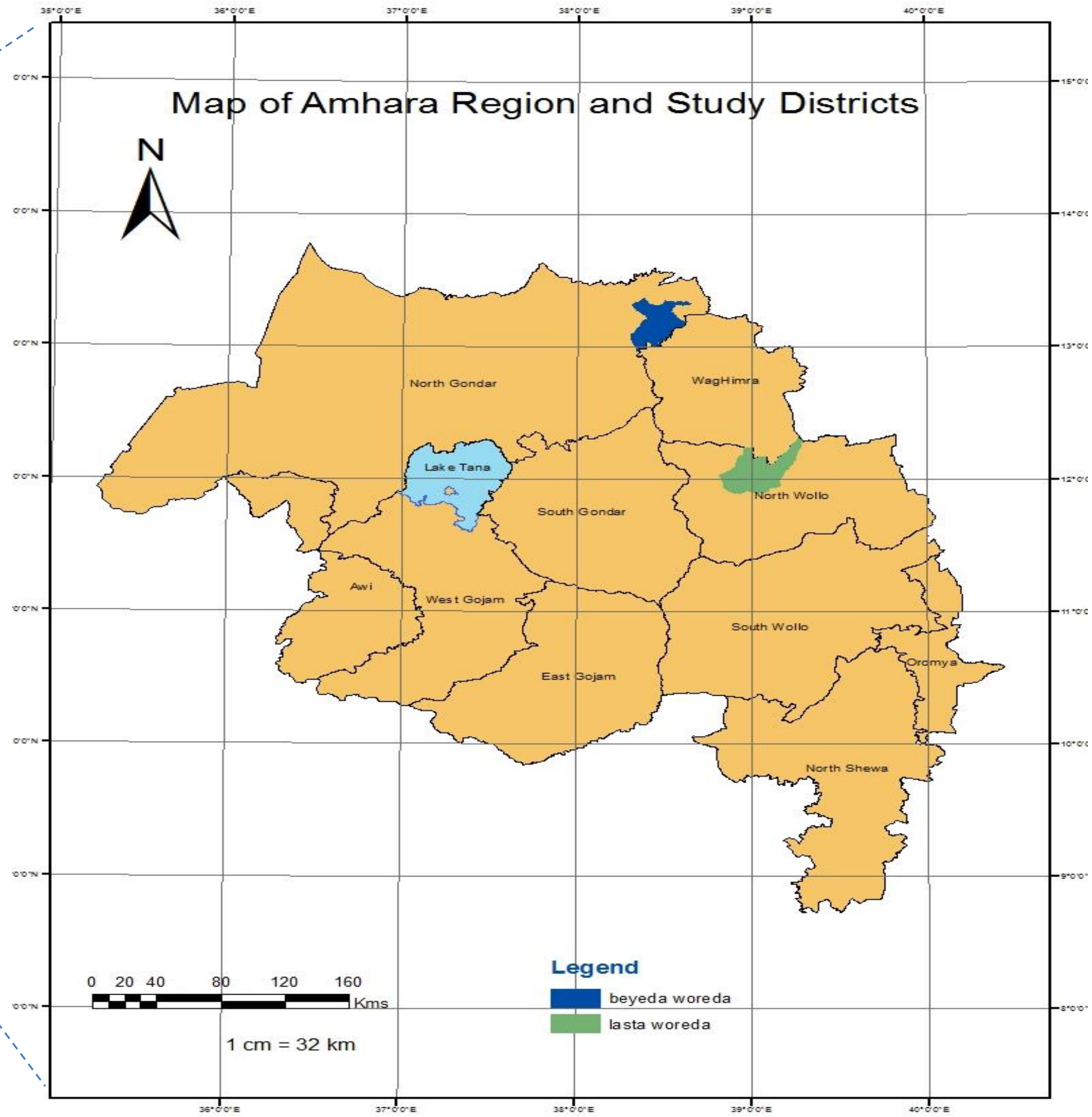
**Table 2: Biophysical and socio-economic characteristics of study areas**

| Characteristics | Lasta | Beyeda |
|---|---|---|
| Biophysical characteristics | | |
| Altitude | 1400-4200 | 1900-4437 |
| Annual mean temperature (°C) | 16-21 | 8-20 |
| Annual mean rainfall (mm) | 600–900 | 1172–1700 |
| Dominant soil type | Leptosol and Vertisols | Vertisols |
| Topography | 50 % mountainous | 70 % mountainous |
| Socioeconomic characteristics | | |
| Total population (2012) | 129,464 | 105,482 |
| Area in km2 (2012) | 1119.35km$^2$ | 973.05 km$^2$ |
| Population density (per Km$^2$) | 115.7 | 108.4 |
| Arable land | 70,163 ha | 43,562 ha |
| Distance from regional capital | 260 km | 410 km |
| Production activities | | |
| Farming system | Northeast Mixed Cereal | North Highland, barley & sheep |
| Major food crops | Sorghum, teff and barley | Barley, wheat and beans |
| Livestock | Cattle, goat and sheep | Sheep, cattle & horse |
| Food insecure population (2009) | 42,356 | 40,610 |

Source: Documents review, district Agriculture and Rural Development Offices (2013)

**Figure 1: Map of the study region and location of districts**




Source: Plotted using Arcmap10. GIS data/shape files/ provided by Amhara region Agriculture and Rural Development office

## 4.2.Qualitative Research Methodology

Qualitative research approach is concerned with life as it is lived and things as they happen. In other words, it seeks lived experiences in real situations (Creswell, 1994;Gerson & Horowitz, 2002). The main interest in qualitative research lies in the meanings people attach to their actions and on their perspectives and understandings of a particular issue or problem.

Most qualitative research follow inductive inquiry, which often starts with a collection of data and empirical observations and attempts to formulate “abstractions, concepts, hypotheses, and theories from details”(Creswell, 1994:145). Similarly, Glaser, Strauss, and Strutzel (1968) note that qualitative research is mainly motivated by the pursuit of generating a theory from data in what they referred as the Grounded Theory approach because the theory is found within the social activity it seeks out to explain.

The other basic assumptions underpinning qualitative research design are its primary concern with processes-rather than outcomes and its focus on fieldwork “where the researcher physically goes to people, setting, site or institution to observe or record behaviour in its natural setting”(Creswell, 1994:145). Similarly, this study uses qualitative methodology as it intends to capture how smallholders in rural Ethiopia are affected by climate variability and change and aimed to explore the perceptions and experiences of smallholders in their actual setting through conducting fieldwork.

The rationale for using qualitative research design in this study stems from the type of research questions posed and the relative advantages that qualitative research method, particularly, in terms of capturing the trends and processes of issues such as livelihood diversification and adaptive capacity and perceptions on climate change in detail. A quantitative approach allows for testing specific hypotheses, establishing causality of an impact of given variables on certain outcomes, and for making generalizations about large populations on the basis of representative samples. On the other hand, qualitative research provides detailed attention to a context and brings out explanations to 'why' and 'how' questions that facilitate the understanding processes (Rao & Woolcock, 2003). The qualitative case study brings to light issues that are not amenable to quantitative analysis, such as perceptions of smallholder farmers to climate change and how and why they choose certain diversification strategies over others.

### 4.2.1. The Case Study Design

The study adopted a case study design as a qualitative methodological approach that combines several data gathering methods in a single study (Berg, Lune & Lune, 2004). This particular design is chosen as it involves "systematically gathering enough information about a particular person, social setting, event or a group to permit the researcher to effectively understand how it operates or functions" (Berg, 2001:225). Case studies are also suitable for investigating "how" and "why" research questions and contemporary issues or events within a real life context (Yin, 1984). Thus, a case study has the advantages of opening-up the way for discovering conceptual relationships or patterns and formulating hypothesis that may be pursued in subsequent studies (see Gomm, Hammersley, & Foster, 2000). May (2002) citing Marshall and Rossman (1989) also note that the purpose of the case study is to chart, depict and characterize events and activities, which makes it all the more suitable approach to studying diversification that involves engaging in multiple activities. Moreover, case study design fits the purpose of the study that has a focus on a particular group and setting – smallholder farmers in rural Ethiopia and sets out to explore a contemporary issue–climate change perception and adaptation.

The major limitations of the case study approach relate to concerns with the inability to draw generalizations based on few cases and the accumulation of "too much" data from different sources that not only tend to take relatively longer time analyse but also result in the risk of poorly organised data (Yin, 1984). These problems can result in lack of rigor and allow "equivocal evidence or biased views to influence the direction of the findings and conclusions" (Yin, 1984: 21).

These limitations can be addressed by developing concepts through a literature review and use of multiple sources of evidence (triangulation), using proper sampling techniques, and procedures in selecting participants for the study. In this study, all these measures were taken to ensure construct validity allow for a robust "substantiation of constructs and hypotheses that assists in generalizability of the research findings" (Bonoma, 1985 as cited in Christie et al., 2000:16). In order to ascertain internal validity, strategies such as linking analysis to an existing theory, cross-checking the consistency of information collected, and organizing the data into descriptive themes that keep track of the research questions (Yin, 1994) were used.

The next section discusses the data collection procedures, instruments and sampling techniques which give further evidence of how rigor is achieved in the study.

**Table 3: A summary of the major categories of case study approach**

| Author | Categories | Main features |
|---|---|---|
| Yin(1984) | Exploratory | Seeks to explore any phenomenon in the data which serves as a point of interest to the researcher to open up the door for further analysis of the phenomenon observed. |
| | Descriptive | Aims to describe the natural phenomena which occur within the data. |
| | Explanatory | Examines the data closely in order to explain the phenomena in the data. On the basis of the data, the researcher may then form a theory and set to test this theory. |
| Stake(1995)<br>Berg (2001) | Intrinsic | Examines the case for its own sake to gain more understanding of the case. It is conducted when the unit of analysis portrays some unique characteristic or problem which was not explored before. |
| | Instrumental | Are conducted to provide insights into an issue or refine a theoretical explanation. |
| | Collective | Uses several instrumental cases to permit better understanding or even improve the ability to theorize about a broader context. |

The present study follows an approach that is close to both the descriptive and instrumental types of case studies. It seeks to yield detailed description of qualitative accounts, which then help to enrich our understanding of how smallholders perceive and respond to climate change and possibly expand the literature on local adaptation to climate change.

### 4.2.2. Sampling Strategy and Data Collection Techniques

Data for this study came from a combination of different data collection techniques applied during the intensive fieldwork period from May to August 2013, which included semi-structured interviews with key informants, Focus Group Discussions (FGDs), direct field observation and some Participatory Rapid Appraisal (PRA) techniques conducted with study participants such as wealth and problem ranking matrix, time-line exercises and seasonal calendar. Throughout the fieldwork period, some tape-recording combined with note-taking was used to capture all interviews with key informants and group discussions.

#### 4.2.2.1. Sampling Strategy

The case study research design adopted two sampling strategies namely, purposive and snowball or chain sampling. For the most part, the study relied on purposive sampling which was implemented at different stages of the sampling units selection including the selection of study areas.

Purposive sampling is the most commonly used qualitative research sampling strategy in which sample units are selected owing to their particular characteristics to meet the goals of a research (Ritchie et al., 2013). In purposive sampling, the decision to choosing a sample is made with the aim of bringing a group of respondents who are strategically located to shed light on the issue/problem under investigation (May, 2002). This process allows for flexibility and diversity in the sampling procedure and makes it easy for researchers to take advantage of opportunities that may enrich the research agenda (Patton, 2005).

In this study, purposive sampling is used to select sampling units, mainly smallholder farmers by going through a published list of smallholders obtained from the administrative records of each *kebele* (village) as a sampling frame. Then, a snowball or chain Sampling is used both as a sampling technique and another way of generating a relatively brief and manageable sampling frame. Thus, Development Agents (DA) and farmers already interviewed were asked to identify others who can provide information on the research topic.

As the issue of climate change requires that people discuss conditions based on recall, we selected participants for both for the key informants interviews and FGDs based on a mix of pre-defined criteria such as being born in a particular village or lived there for not less than three decades; have a first-hand experience of climatic shocks (e.g drought); and are knowledgeable about their local environment, weather patterns and climate. Moreover, in order to ensure diversity in opinions, efforts were made to include young age and female participants. Accordingly, the final sample is composed of eight women and people with the age group ranging between 28 and 72. The size of a sample in purposive sampling is determined on the basis of "theoretical saturation" (the point in data collection when new data no longer provide additional insights to the research questions) (May, 2002; Patton, 2005).

#### 4.2.2.2. Data Collection Techniques

**Key informant Interviews**

A key-informant interview can be anything from a formal interview with a semi-structured questionnaire to a short conversation with a local leader in a village. The defining feature of key informants is that they are knowledgeable individuals who can provide information about an issue and local situations (Marshall, 1996).

The key informant interviews were employed using semi-structured interview schedules, for topics prepared to guide specific questions during the interview. For instance, key informants were asked if they had experienced any change in their local climate with regards to increase in temperature, reduction in rainfall or changes in the onset and offset of rainy seasons in the last three decades. Other topics covered in the schedule include local indicators of the change if farmers perceive any changes; types of diversification strategies and challenges and prospects for pursuing non-farm activities (see checklists for interview topics, annex). The main advantage of using semi-structured interviews is that it helps to capture, describe and discuss the respondent's own ideas, opinions and experiences (Silverman, 2001; Patton, 2003).

Two-types of semi-structured interview guides were used and administered to two groups of informants–local farmers and agriculture and rural development experts in the two districts and in the region. The key informants were purposively selected on the basis of their knowledge of their local climate and livelihood dynamics as well as expertise and experience gained in working closely with smallholders in the region. Accordingly, four smallholder farmers from *Medage* and *Nakute-leeab* villages of Lasta district and *Watti* and *Ayiga* villages of Beyeda district were selected as key informants based on the information furnished by two Development Agents (DAs) that work with farmers in the districts by relying on snowball sampling technique. The DAs knew farmers who can provide the required information and identified potential interviewees as people who are either born in their respective villages or have lived in their villages for more than three decades in order to be able to provide context-specific and detailed information on the topics.

Moreover, other interviews were conducted with an expert from Amhara region Food Security Coordination Office, an officer from the region’s Agriculture and Rural Development office and two Food Security and Disaster Preparedness coordinators from each district. These interviews were instrumental in providing critical information on the nature of climate-induced shocks and the major patterns of livelihood activities in the districts. The interviews also paved the way to identifying and accessing key documents relating to the issues raised and guided the documentary analysis that followed the key informant interviews. All interviews were conducted by the lead researcher and two assistants who helped in taking-notes, tape-recording, and in probing on issues that require further clarifications, particularly for the interviews conducted with smallholder farmers. These research assistants were recent graduates that majored in Sociology and required only refresher training on how to conduct semi-structured interviews and on the structure and purpose of the interview schedules.

**Focus Group Discussions**

Focus Group Discussion (FGD) is a type of conversation conducted in an informal setting that aims at gathering data on topics of interest. It is chaired by a leader or researcher and allows group interaction such that participants are able to build on each other's' ideas and comments to provide in-depth views not attainable from individual settings. FGDs have the merit that unanticipated remarks and new perspectives could be explored easily while discussing issues (Robson, 1993; Bloor et al., 2001).

Three FGDs were held, one in Beyeda and two in Lasta districts, involving 26 farmers. The discussions were chaired by the lead researcher with the help of two assistants who took notes and moderated the discussions. The topics of the FGDs principally focused on farmers' perception on climate variability and climate change in their locality; assessment of the risks of climate variability and change on their livelihoods, and ways through which farmers adapt to climate variability and change. The FGDs were composed of members with different age and sex groups, selected purposively since the research goal requires gaining different perceptions, verify opinion and attitudes from groups to help elaborate clarify and counter-check ideas and experiences that were obtained through other methods.[6]

[6] Bloor et al. (2000:20) suggests running separate groups in cases where participants of the FGD include people who are likely to hold radically opposed views. This may also facilitate comparison without the need to run disruptive and distressing groups.

## Direct Observation

Through transect walk, the researcher observed the overall economic and social conditions of the selected villages. This method particularly helped to notice how climate variability has impacted the study villages and complemented the information gained from documents and key informants.

## Participatory Rural Appraisal (PRA) Techniques

In addition to the key informant interviews and FGDs, some Participatory Rural Appraisal (PRA) techniques were implemented. PRA is a way of learning from and with community members with the aim of gaining a better understanding of the issue (see Chambers, 1994). These techniques have recently been used in climate change adaptation studies and proved to be valuable in enriching results from other methods(van Aalst, Cannon, & Burton, 2008; Filho, 2011).

The PRA techniques used in this study include (1) participatory wealth-ranking exercise, in which focus group discussants at the end of the session were encouraged to enlist different wealth indicators in their villages. These were then organized into a wealth matrix based on the indicators that most participants agreed on and helped to identify wealth groups (2) Historical timeline: to gather information on major climatic events that occurred in the villages (3) Seasonal calendars and problem ranking matrix were conducted with farmers from Lasta district to gain information on livelihood trajectories and major stress and vulnerability sources.

### 4.2.3. Data Analysis

In the qualitative analysis, data collection and analysis often proceed simultaneously (Creswell, 2002). The qualitative data obtained through the key-informant interviews and FGDs were coded and analysed using the general inductive approach, which is a systematic procedure for analysing qualitative data where the analysis is guided by specific objectives. According to Thomas (2006) the main purposes of an inductive approach to data analysis are to reduce extensive and diverse raw text data into a concise summary format, establish links between the research objectives and the summary findings derived from the raw data. This may be used to develop model or theory about the underlying structure of experiences or processes which are evident in the raw data.

Following, Creswell (2002) the following specific steps were taken in the analysis of the data (1) preliminary exploration of the data by reading through the audio transcripts and written memos; (2) coding the data by segmenting and labelling the text; (3) using codes to develop themes by aggregating similar codes together; (4) connecting and interrelating themes; and (5) constructing a narrative.

During the data collecting phase, the lead researcher kept field memos about intuitions concerning emerging patterns and themes. A rigorous and systematic reading and coding of the transcripts also allowed major themes to emerge. Interview texts then were coded to allow for such thematic analysis in line with the major research questions. In doing so, emphasis is laid on the documentation of relationships between themes and the identification of issues important to study participants. Moreover, similarities and differences across individuals, groups and villages were also explored.

Confidentiality is the main ethical issue given due consideration throughout the data collection phase, particularly as there was some information assumed to be of personal opinions of farmers, government officials and experts. Thus, pseudonyms were proposed to replace the name of respondents' who feel uncomfortable to be mentioned by name.[7] Moreover, prior to the interviews and FGDs letters seeking informed consent were presented and read to all respondents.

The farmers' perceptions of climate variability and change were compared with rainfall and temperature records obtained from the nearest weather stations of Debark and Lalibela from the National Meteorological Agency (NMA) of Ethiopia. These data were monthly records of rainfall and maximum and minimum temperature for the period 1989–2011 for Lalibela/Lasta and 2000-2011 for Debark/Beyeda. Rainfall variability was calculated using the coefficient of variation (CV) on both year-to-year basis (inter-annual variability) and for the whole period and linear regressions and Mann-Kendall trend tests were used to detect trends on temperature and rainfall data. The following section briefly discusses the methodology used in trend analysis.

### 4.3. Trend Analysis of Climate Data

Trend refers to the rate at which temperature or rainfall changes over a time period and it is often determined by the relationship between these variables and time (Deshmukh & Lunge, 2013). The magnitude of trend in a time series can be determined by parametric tests (using regression analysis) or non-parametric tests (e.g. Mann-Kendall trend test). This study first implemented linear regression model to test the existence of trend on both temperature and

[7] However, pseudonyms are not used in this paper, as there were no respondents who harboured such concerns.

rainfall data and then used the Mann-Kendall trend test on data that have shown a reasonably higher R-square to check the significance of the trend. Accordingly, a trend could only be detected for the annual mean maximum temperature data from the two districts.

The linear regression analysis is used with time as the independent variable and temperature or rainfall as the dependent variable. This method is extensively used in climate change studies (see Shrestha et al., 1999; Stafford et al., 2000; Cheung, Senay, & Singh, 2008; Río et al., 2011; Jain & Kumar, 2012). The linear regression model is given by:

$$y = \alpha + \boldsymbol{\beta X} + \boldsymbol{\varepsilon} \qquad (1)$$

where, $y$ is mean maximum temperature (the dependent variable);

$\alpha$ is the intercept;

$\boldsymbol{\beta}$ is the coefficient of the explanatory variable (the slope)

$\boldsymbol{X}$ is the independent variable (time) and;

$\boldsymbol{\varepsilon}$ is the stochastic term (the residual)

The linear trend value is represented by the slope of the simple least-square regression line. The linear regression model makes strong assumptions about the distribution of the dependent variable ($y$) over time. These assumptions mainly apply to the residuals being normally distributed, independent (with no serial correlation), and identically distributed (with constant variance) (Helsel & Hirsch, 2002; Frei, 2014)[8].

[8] The classical linear model assumptions of strict exogeneity and no serial correlation for a time series data are highly restrictive and may be unrealistic (Wooldridge, 2008).

In most cases, climate time-series data are assumed to consist of a long-term trend component and a white noise residual component (i.e. with no serial correlation) (Wigley & Jones, 1981; Frei, 2014). In practice, due to the multi-year existence of natural climate variability (Zhang et al., 2000), errors from adjacent time periods may be correlated across time. In this context, assuming white noise residuals may result in overestimating the significance of the trend (Wooldridge, 2008).

Therefore, after checking the model for the critical assumptions, the t-test (parametric test) is used to assess whether the slope's coefficient of the fitted linear regression is significantly different from zero, indicating the presence of a linear trend.[9] The null hypothesis for the test is that $\boldsymbol{\beta} = 0$ (data not linearly dependent on time) and the alternative hypothesis is $\boldsymbol{\beta} \neq 0$.

The test statistic (linear regression T-Test) is given by:

$$t = \frac{\beta}{\dfrac{\sum\left(\mathrm{Y_i} - \hat{\mathrm{Y}}_\mathrm{i}\right)^2}{(\mathrm{n}-2)\sum\left(\mathrm{X_i} - \overline{\mathrm{X}}\right)^2}} \tag{2}$$

where,

$t$ is distributed like students' t with $n$-2 degrees of freedom and n is the sample size (Frei, 2014).

Following Yue and Hashino (2003) and Jain and Kumar (2012), the non-parametric (distribution free) Mann–Kandall (M-K) test has also been applied to assess the significance of monotonic trend. The test also confirmed the existence of significant upward trends in annual mean maximum temperature in the two districts (see annex for the details on M-K test).

9 We used Portmanteau test for white noise in Stata to check for autocorrelation. Maximum temperature data from both districts have passed this test showing no serial correlation. These data also passed the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity (see **Table C**, annexed).

## 5. Results and Discussions

This section presents the results from the qualitative interviews, the FGDs and the statistical analysis of meteorological data organized in three sub-sections– perceptions, effects of climate variability and change, and local adaptation strategies.

### 5.1. Farmers' Perceptions of Climate Variability and Change

On the issue of climate variability and change, respondents in both districts stated that they perceive increased temperature and erratic rainfall patterns in the last two decades. They all seem to agree that the short rains (Belg) are becoming more erratic and almost unreliable for Belg-crop production. The year 1984 is frequently mentioned as a turning point for these changes in the Belg rains in Lasta district. The changes are mostly well-perceived by Lasta district respondents, perhaps because most smallholders in the district heavily rely on the Belg rains for growing crops that are mostly referred locally as " belage" such as sorgum, millet and maize. The focus group discussants and key informants have also indicated that such variability in rainfall patterns are increasingly becoming part of the long-term climatic trends in their areas, with pronounced delays frequently observed in the starting dates of the *Kirmet* rains and increasing temperature during *Bega* (the dry season) from October–February. For instance, farmers in Lasta district often used the word " berha" which can be roughly translated to mean 'desert, unsuitable for both farming and livestock rearing' to refer to the recent climatic change in their villages. This implies that farmers perceive an unusual weather patterns and take this a sign that some irreversible process of change is underway in their local climate which already altered what they think is 'normal' (See **Box 1**).

When asked to provide some specific indicators, farmers gave interesting details about the increasing warming trend that they observed in the recent five years, with the daily as well as night temperatures increasingly felt above normal for the dry season. The terms that are frequently used to describe the increase in temperature are “too hot” and “unbearable”. More than the temperatures changes, however, farmers have markedly focused their discussions on the changes in rainfall patters as their livelihood depends on a rain-fed agriculture. Accordingly, FGD participants in Lasta district highlighted that the rains are coming late and stopping early during the main rainy season (*kiremet*).[10] Key informants and elders during the FGDs indicated that in the earlier times, mostly two and three decades ago, the kirmet rains used to start as early as 12$^{th}$ June and keep on raining well into mid-September. However, this pattern is reported to be slowly changing with the rains coming late, being erratic and stopping too early (sometimes in mid-August). Thus, more often than not, respondents expressed the Kiremet rains as a “fickle friend”. It is true that uncertainty is an integral part of being a farmer everywhere. However, some degree of weather predictability is important, even more so in subsistence agriculture that depends heavily on the rains. The Belg (short rains) are also perceived to have shown greater variability and at times do not come at all.

In Beyeda, respondents noted that the change in temperature is somehow a recent and an abrupt phenomenon. According to group discussions, for much of the Bega season, they experienced several days with temperatures oscillating between cold (in the mornings) and very hot (in the afternoons). Such conditions are indicated as deviations from what used to be normal in the past five to ten years. With regards to the rains, similar trends are reported, with greater variability in the regular pattern of rains both in the *Belg* and *Kiremet* seasons.

[10] Kiremet is the Amharic name mostly used for the main rainy season in much of the Ethiopian highlands. The rains mostly start in June and stop in September.

**Box 1:** Farmers' perceptions on climate variability and change (In-depth interview, 2013)

"In recent years, the *gamen* [a local term for extreme temperature] is becoming unbearable and we all are suffering from the extreme heat. We [the elders] spend time with our flocks of sheep in tree shades yearning for the Belg rains to give us some respite from the long dry spells which seem to stay forever. In the old days, this area used to be Dega [cold] and wet and we used to put on *koborta* and *gabbi* [locally knitted clothes thick and warm enough to be used as blankets or cloaks] even for the day time. But now, it is even too hot to put on *Netella* (very light cloth)" Biru Legesse, 72 male, from Mahil Deber village, Nakuteleaab, Lasta district.

Another key informant, Mengiste Welde, in his mid-fifties fromWatti kebele, Beyeda, recalls the change in climate by comparing it to the last two decades. His narration also reveals the impact of the change and the desperation in his community:

"Since I came off age, I have never seen such a drastic change in the temperature. Back when I was a child, this place used to be very cold and rainy; in fact I even recall that our fathers used to plant crops as early as March, almost right after they finished harvesting their *Meher* crops. That was a time of plenty except for the occasional miseries caused by pestilence and we did not know droughts and lack of rains. Today, however, the rains are not coming regularly in June and I have sadly witnessed the bitter reality that the rains have begun to fall in mid-July. To make matters worse, when the rains fail, it comes with a vengeance, pouring its content once, battering the soil mercilessly and washing it away leaving us with bare rocks and gravels"

When asked about the possible causes of these changes, respondents gave similar opinions highlighting mainly environmental degradation such as deforestation, erosion and mismanagement of water and soil resources. Interestingly, most farmers take the blame for the environmental degradation and relate it to their own actions such as cutting down trees and ploughing hill sides that intensify run-off and soil erosion.

In both study districts, key informants and focus group discussion participants came up with some interesting and locally relevant indicators of change in the climate. Some have described how temperature increased so much so that food and beverages can no longer be kept for days and have to be prepared and consumed right away.

For instance, Haregnesh Takele, 34 and mother of three from Nakute Leeab village, Lasta district, described her situation as follows: " …in the past [15 years ago, she specifically mentioned the time before she got married] the *injera* that we bake used to stay fresh for about four to five days.[11] But, recently it is forming mold in two days because of the sweltering heat."

Similarly, another 45 years old woman, FGD participant from *Watti* kebele, Beyeda district, Zelekash Nigussie, notes that "I make a living by selling *Tella* [home-brewed beer prepared from barely, hops and spices] and in recent years, I am losing income because of the unbearable heat during the dry season, the *Tella* that I brew is falling out of favour since it is fermenting too warm, giving it a bad taste."

These responses indicate that women are keen on identifying local climate change indicators that have direct bearings on their day-to-day household chores. The effect of climate variability and change on women is discussed in section 5.3.

Farmers in the study areas have also mentioned an increase in the frequency of droughts and hot spells. In Lasta for instance, participants of the two FGDs almost equivocally agree that droughts are occurring every three to five years since the mid-1990s. The word "berha" meaning wasteland has been used more often to refer to the harsher climatic conditions that the farmers are facing. In Beyeda, rainfall patterns are perceived to have changed both in

[11] *Injera* is a staple food in many parts of Ethiopia. It is a sourdough-risen flatbread usually made out of *teff*, millet and/or sorghum.

timing and duration causing frequent flash floods, aggravating the problem of land degradation.

The focus group discussions, in-depth interviews, as well as information obtained from the districts Agriculture and Rural Development (ARD) offices yielded the following indicators:

- delayed onset of both Belg and Meher rains as well as high variability, and short duration and high intensity of rains;
- an increase in daytime and night time temperature during the Bega season (from October to January). This is particularly felt by Beyeda residents who recalled very cold weather even during the dry season;
- increase in the frequency and intensity of droughts in both districts;
- an increase in flash floods in Beyeda district due to high intensity of rainfall in the mountains causing high run-off.

## 5.2. Results from Climate Data

Climate data were obtained from the Ethiopian National meteorological Agency for the nearest stations for the two districts. The data for Lasta are obtained from Lalibela station which recorded rainfall and temperature measurements since 1989 with brief interruptions during the change in regime from 1990 to end of 1991. For Beyeda, records from Debark station, available for the period 2000– 2011 were used.[12]

[12] Despite the availability records since 1974, temperature and rainfall data for the Debark station prior to the year 2000 are patchy with many missing data points and are unsuitable for trend analysis.

The two districts are characterized by a bi-modal climate type with 'Belg' or short rains from February/March– June and 'Kiremt' main rainy season that extends from June/July to September.

### 5.2.1. Rainfall Records and Farmers' Perceptions

Total rainfall in Lasta during the period (1989–2011) showed little inter-annual variation ranging between 338 and 1002 mm (CV=26.3 %). Looking at the inter-seasonal variation however gives a different picture. Hence, rainfall in the *Belg* season (short rainy season) shows a high variability fluctuating between 23 and 310.9 mm (CV=61 %). The *Kiremet* season rainfall also varied between 153.4 and 893.6 mm but with relatively less rate (CV=34.5 %) (See **Table A**, annexed).

In Beyeda inter-annual rainfall varies between 810–1357 mm (CV=14.4 %). The Belg season rainfall shows high variation between 41.2 and 219.6 mm (CV=54%). The kiremet rainfall has an inter-annual variation of 740 and 1198 mm (CV=13.8 %). Compared to Lasta, rainfall in Beyeda shows lesser anomaly from the ten-year average with nine out of the 12 years showing irregularity. In Lasta, over the 21 years period, (1989–2011) 19 years show irregularity (i.e. 90.5 % of the time).

In general, inter-seasonal variations are high for the Belg (the short rains) and show a marked anomaly in the two districts but do not show any measurable trends. Conway (2000) also found no trend in annual rainfall for the period 1950-2000 from Combolocha and Dessie (stations that are close to Lalibela). This lack of robust trends in rainfall data is also reflected in other analyses at a national level (see FDRE, 2007; Regassa et al., 2010). Similarly, this paper detected no trend in the analysis of rainfall records from 1960 to 2006 using the UNDP data from McSweeney et al. (2010).

There is some parallel between the perceived seasonal variability patterns of the rains and the observed records of rainfall data in the two districts especially for the Belg season. However, unlike farmers' perceptions, which indicate a decrease in rainfall amount, the rainfalls records show no significant decline. For instance, farmers in Lasta have identified the years 2002 and 2005 as drought years (see **Table B**, annexed) and the rainfall records also show that the rains for both the Belg and Kiremet seasons show reductions for the years 2002 and 2004 as compared to previous years. However, this is not true for all cases. For instance, for the year 2005, unlike the farmers' perceptions, the rainfall records show that in relative terms, the amount of rainfall did not show a reduction. This indicates that there is some divergence between farmers' perceptions and the rainfall records and points out the important but subtle difference between farmers' perceptions and climate records. That is to say, farmers' perception is mostly influenced by their experience of irregularities in the patterns of rains like the onset, duration, and exit of the rainy season rather than on the amount of rain. Such information is lacking in the rainfall records that only measure the total amount of rain for a given period. Such focus on the timing of the rains makes farmers' perceptions rich in terms of furnishing important details on the changes in the weather patterns in their locality.

### 5.2.2. Temperature Trends

Average maximum annual temperature in both districts shows increasing trends over the period (2000–2009, for Beyeda) and (1989–2011, for Lasta). These trends were obtained using linear regression best fit lines. The trends with their linear regression equations and coefficient of determinations ($R^2$) are given in **Figure A** and **B** (annexed) and summarized in **Table 4**.

**Table 4: Linear regression and Mann-Kendall statistics results**

| Station | Record period | MT (°C) | OLS cof. | $R^2$ | M-K | S |
|---|---|---|---|---|---|---|
| Debark | 2000–2011 | Maximum | 0.0524* (0.0160) | 0.57 | 0.60** | 27 |
| | | Minimum | -0.0013 (0.0210) | 0.00 | 0.00 | 0.00 |
| Lalibela | 1989–2011 | Maximum | 0.0339** (0.0117) | 0.30 | 0.333** | 70 |
| | | Minimum | 0.013 (0.0121) | 0.06 | 0.28 | 54 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: computed from NMA data.

*Notes:*
MT= Mean Temperature
OLS cof.= Ordinary Least Square coefficients that measure the effect of time on temperature.
M-K= Kendall's tau
S=M-K test statistic or the Kendall score

Temperature in Lasta has increased by about 0.035 $^0$C every year since 1989 and there has been a warming trend in the annual maximum temperature over the past two decades. In Beyeda temperature has increased by 0.05 $^0$C per year between the year 2000 and 2009.

These positive trends also correspond to farmers' perceptions of changes in day-time (maximum) as well as night-time (minimum) temperature.

In sum, the statistical analysis of rainfall and temperature records from the two sites show that temperature is increasing while there is no significant decline in rainfall amount. This result corroborates with climatological studies that analysed long periods of rainfall and temperature trends in Ethiopia (see Conway, Mould, & Bewket, 2004; Seleshi & Zanke, 2004).

## 5.3. Effects of Climate Variabilty and Change

Frequent droughts and occasional floods are the main climatic hazards identified by respondents in the focus group discussions and the PRA timelines in Lasta (see **Table B**, annexed).These climatic risks have caused loss of crops, livestock, farmland, disrupted livelihoods, and resulted in increasing food insecurity for households. In Beyeda on the other hand, no significant drought or flooding event is mentioned by participants except for the occasional hot-spells and unseasonal rains that result in flash floods.

Participants of FGDs in Lasta discussed that frequent dry-spells in the rainy season is affecting the production of meher crops, mainly *teff* [13] which they say have shown a reduction in yield in recent years. The late onset of the Belg season rains is also mentioned as the main factor for reduction in the production of millet and sorghum. A Key informant from Lasta said:

> "The main problem [with the recent change in the climate] is the lack of rains in May and April [the Belg rains]. We spend so much time preparing our land and sow maize, and millet hoping that the rain would come. But the rain will come late causing crop failure. The Kirmet rains stop early which is bad for the teff crop and in early October the wind and the frost conspire to damage whatever little crop that is left standing on our farms, leaving us with so little to feed so many mouths." (Teklu Abebe, 28 from Madage village, Lasta).

[13] *Eragrostis tef* is a native cereal to the Northern Ethiopian highlands that is a major ingredient to make *Injera*- a staple food for most people in the country.

FGD participants from Beyeda also indicated that hail storms and frost, coupled with more erratic and untimely rains, are destroying barley and wheat crops.[14] Some discussants mentioned the increase in temperature as a positive development and a respite from the extreme cold weather in the past. However, all discussants agree that the increase in temperature along with variability in rainfall poses a risk to their livelihood particularly during the growing season.

Almost all participants of the FGDs mentioned an increase in the occurrences of livestock diseases in their villages, associated with the increasing temperature and lack of water. Discussants feel that some new livestock epidemics are affecting their cattle. However, most of them failed to provide logical explanations on the causal relationship between increasing livestock epidemics and change in temperature and rainfall patterns. In this regard, a few of the FGDs participants were able to come up with somewhat plausible explanations that show the possible effects of high temperature on livestock health by citing how the high temperature creates a favourable condition for the breeding and subsequent spread of some skin diseases among herds of cattle.

Key informants from Agriculture and Rural Development (ARD) offices indicated that the change in climatic conditions mainly affect livestock health through reducing the availability of fodder and water making them more susceptible to diseases. They cited a recent infestation of tick-borne diseases that causes lumpy skin disease (locally called *gureb-reb*). Other common types of diseases that affect livestock in study villages include foot and mouth

[14] Interestingly, some local farmers claim that in the past (20-30 years) the mountain peaks used to be covered by snow throughout the year. However, an earlier study by Simoons (1960), assert that although snow falls in these mountains, there is no permanent snow all year round. The author cites estimations that put the snow line to be at about 4800 meters, more than *Ras Dashen*– the highest mountain in Ethiopia. In addition, the Amharic name which is often used to indicate hail is ‘beredo’ but this does not necessarily refer to snow but to hail stones, which are very common during the rainy season even in the low lands.

disease and *Aba-senga* (anthrax). The main impacts of climate variability and change on agriculture are summarized in **Table 5.**

Respondents in Lasta indicated that the incidence of Malaria in the low-lying (kola) villages showed a marked reduction in recent years. Most of the respondents relate this to the frequent dry-spells and shortage of rainfall. Accordingly, they stated that as rainfall became more erratic and reduced in volume, it fails to replenish the numerous ponds around the village that the mosquito flies reproduce. All these could be taken as an indication of the on-going climatic stress that can have a long-term impact in altering the ecosystem, possibly to arid environment. The following quote from a male FGD participant illustrates all too clearly the change in climatic conditions and its effect on the ecosystem.

> "In the old days, after the rainy season, water used to lay still in the low-lying fields until November, leaving behind ponds surrounded by tall grasses. Nowadays, we no longer hear the familiar sounds of frogs croaking and mosquitos buzzing at night. For me, this reflects how nature has turned its grim face on this village, turning it to wasteland, dry and unforgivingly harsh for even the smallest creatures that do not need much to subsist" (Woday Sitotaw, 45 from Nakutelaab village, Lasta district).

Women FGD participants have highlighted how the frequent droughts are affecting their livelihoods. They indicated how higher temperature means that food (*injera* and stew) has to be consumed immediately now, placing a greater burden on women and girls who expend more energy on cooking more frequently. Moreover, the greater distance to collect water has further increased the social reproductive burden they carry. Women and girls have to walk long distances to fetch water, since most nearby water springs and ponds have dried-up. This clearly shows how climate variability and change is adding further challenges to women who are already poor and struggling. Hence,with the advent of more changes in the climate, the socio-economic inequality that women face is likely to compound their vulnerabilities to the effects of climate change. This condition is also highlighted by United Nations Women Watch fact sheet which states “women are more vulnerable to the effects of climate change than men primarily because they are poor and are more dependent for their livelihood on natural resources that are threatened by climate change” (UN Women Watch, 2009:1).

**Table 5: Effects of Climate Variability and Change on Agricultural Activities in Lasta and Beyeda**

| Climatic factors | Perceived impacts | Cases |
|---|---|---|
| Increased temperature | Increased hot and dry-spells affecting crop and livestock production.<br>Increased pest and disease incidences | Crop failure teff, *ageda-korkur*( maize stalk borer) affecting maize and sorghum and plusia warm affecting barely and sorghum in Lasta. *Yegebs kish-kish* ( barley Aphid; Russian wheat Aphid) affecting barley & wheat in Beyeda. |
| Delay of onset of rains and early set-off | reducing length of growing period. | frequent crop failures in Lasta are associated withthe delay in rainfall both in the *belg* and *kirmet.* |
| Unseasonal rains | Damage to standing crops. | A few cases are reported during the dry season in Beyeda |
| Increased frequency and magnitude of drought and floods | Drought results in lack of water and fodder for livestock, crop failure. Flash floods cause livestock death & destroy homes and farmlands | Droughts are more frequent in Lasta. Crop pests, animal diseases, and loss of income from damages to crops and livestock is reported in both Lasta and Beyeda. |

Source: Key Informant Interviews and FGDs, 2013.

## 5.4. Diversification as an Adaptation Strategy

Climate variability and uncertainty for years have prompted farming communities to adapt to dynamic environmental and weather conditions. The maintenance of a diversified resource or income base is a prerequisite for adaptation to climate variability as it helps reduce vulneability by spreading risk (Kelly & Adger, 2000). Diversified livelihood systems also allow farming communities to draw on various sources of food and income and reduce vulnerability to climate change (Macchi et al., 2008:18).

In view of this, the paper attempts to identify and analyse predominant livelihood diversification strategies in the districts. As in the case for most rural parts of Ethiopia, people in the districts rely largely on mixed agriculture i.e. crop and animal husbandry as a major source of livelihood. Cereals are the most commonly grown crops in the districts with maize, *teff*, wheat and sorghum being dominant in Lasta and wheat and barley in Beyeda.

FGDs and KIIs respondents have highlighted that there are limited opportunities for diversifying livelihoods particularly in non-farm income earning activities in their villages. Moreover, the existing diversification strategies to a large extent are seasonal and depend on demographic characteristics (mainly age and sex) and wealth category. Thus, key informants from Lasta indicated that the Belg rains are becoming unreliable, adversely affecting the Belg production and income which in turn has forced the youth to engage in seasonal migratory wage labour to neighbouring regions mainly *Raya* ( for agricultural wage labour) and at times as far as *Humera* where there is commercial sesame production. Some of the youth ( both male and female) who have family obligations such as elderly parents to look for, or young children, mostly prefer to engage in “Shekel” or daily wage labour in the nearby Lalibela town mostly in the burgeoning construction sector that pays a daily rate of 35- 40 Birr.[15] The relatively better-off households often engage in profitable activities such as trading oxen, sheep and goats (non-farm activities). The poorest households mostly engage in either the government's public works activities and/or in local wage labour (in weeding, harvesting, trashing etc.) within their village (off-farm activities). Respondents in Lasta identified wealth categories in their villages through the wealth ranking exercise (see **Table D** annexed).

Discussions with the focus group participants revealed that for most households participation in non-farm livelihood activities are mostly limited to manual works like carpentry, masonry, and blacksmith as well as petty-trading such as preparing and selling local food and alcoholic beverages which are mostly pursued by female-headed households that do not own farmland, oxen or do not have enough labour to engage in farming. The other activity which could be categorized as non-farm is seasonal migration, reported to have become more common in recent years mainly due to the expansion of all-weather roads that made once remote areas more accessable to major migration routes.[16]

Some forms of non-farm income earning activities are also available within the emerging small and micro enterprises sector. Employment in the construction and cobblestone works in nearby towns are among the few non-farm opportunities mentioned by group discussants.
However, most poor households are not able to engage in such activities. Even those who are able to participate in these activities do so only for few months outside the growing seasons (October–December) (see **Table E** for the agricultural calendar, annexed). This indicates the

[15] This daily wage rate is apparently barely enough to buy food items required for a daily subsistence from the local (Lalibela) market since the town is a tourist destination and prices are very high. In fact, the amount of cash required to pay for daily meal requirements could reach a minimum of up to 50 Birr.

[16] Although, a very recent phenomenon, International migration to Sudan and the Middle Eastern countries like Saudi Arabia, and U.A.E are becoming common by young girls.

existence of competition for household labour between the two activities since these months are also times for undertaking harvesting and threshing activities.

Thus, households have to make some decisions as to how efficiently allocate their labour between non-farm and off-farm (locally available agricultural wage labour). Moreover, farmers who participate in the public works component of the government's safety net programme are expected to contribute labour for up to six months within their village. As a result, most poor farmers seem to prefer to engage in locally available off-farm activities than engaging in non-farm activities elsewhere (see **Box 2**).

Some respondents from Lasta have also highlighted the role of social capital and distance in making decisions about non-farm activities participation. Accordingly, households who have close relatives in nearby Lalibela town tend to benefit from the non-farm sector than households with no such ties. Those who are located closer to the town and who have some relatives or personal ties (networks) often straddle between the rural and the urban. This phenomenon of straddling the rural-urban divide has long been recognized as an important survival or accumulation strategy in the literature (see Tacoli, 1998; Ellis, 2000). The findings also confirm the role of rural towns (Reardon et al., 1998; Barrett, Reardon, & Webb, 2001; Lanjouw & Lanjouw, 2001) and the positive contribution of social capital in non-farm diversification (see Davis, 2003).

**Box 2: Farmers' view on diversification as an adaptation strategy (In-depth interview, 2013)**

Wende Mequaninit, 35, is from Medage village, Lasta district, married and has two children, completed 6th grade education.

"I have less than half a hectare of land that I mostly use to cultivate wheat. In the last Meher season, I have only managed to harvest 150 KGs, not enough to feed my family for four months. Therefore, I consider myself poor, though slightly better than those who do not have either farmland or able-bodied family members. Since my income from agriculture is barely enough, I always try to earn extra income by engaging in non-farm activities a few months outside the agriculture season. I am participating in the Public Works and contribute labour in the terracing and check-dams construction. Most of the activities involve hard physical labour and one has to work for 15 days per month to earn 19.5 Birr per day. This payment is given in cash for two months and in-kind for four months. I consider the Public work payment very low, but I am not complaining, because I consider it to be a way out of misery for farmers like myself who are able-bodied and healthy. I always dream of going to the big cities like Desse and Addis Ababa to work hard, earn more and live a decent life but I cannot afford that because my kids are too young and I have to support my ailing mother.

The public works last until the end of June. After the rainy season, I take on locally available wage labour usually in harvesting and thrashing [off-farm], earning some cash income, which I use to cover some expenses. The wage rate for such activities varies and depends on the employer's discretion ranging between 20 and 30 Birr per day. Occasionally, I travel to Lalibela and look for wage labour mostly in the construction of houses and buildings earning 35 to 40 Birr per day".

In terms of on-farm diversification, bee-keeping is seen by many of the unemployed and landless youth as an alternative to farming. According to a key informant from the Agriculture and Rural Development (ARD) office of the district, the local government is encouraging the involvement of the youth in this activity and provided trainings, credit as well as land. Thus, it has been observed that these on-farm diversification strategies have begun to bear fruits as some of the bee-keepers have already started supplying their product to the nearest market in Lalibela town.[17] However, they need to find a bigger market at regional or national level since the local market will soon be crowded with more suppliers. Given the high potential of the district in this sector, there is a need for linking producers to external markets.

Moreover, since drought has been a major challenge in Lasta for a long time, people seem to have a high regard for water-harvesting and soil conservation schemes that are being undertaken in their villages through the government’s social protection programme, the Productive Safety Net Programme (PSNP). Though PSNP’s Public Works give more focus to communal activities and less emphasis to activities on private lands, most of the activities, particularly soil and water conservation works are having positive effects on reducing the effects of land degradation. Respondents have noted the long term benefits of the programme in rehabilitating the environment through the watershed management. A Key informant from the Lasta district ARD office also note that area-closure has resulted in an increase in the provision of bee forage as a result of the increase in herbaceous and woody plants. This assessment is also confirmed through direct observation in which the physical structures created through public works such as water and soil conservation, terraces, check-dams, and afforestation can directly or indirectly contribute to increasing households’ and community level adaptive capacity to climate change. Although this needs a broader study that identifies the specific impacts of the programme, it still indicative of the potential effect of the programme in supporting income generating opportunities at least in the context of the study villages.

[17] According to figures obtained from the district Agriculture and Rural Development Office, there were about 1237 organized youth in this activity in 2013.

The discussions with the key informants revealed that because of the attractive prices offered for eucalyptus trees and *Gesho* (hops) at the local market, many farming households have over the past few yearsm began to harvest rainwater to irrigate their land which also helped them to be able to take a steady path towards diversfiying their livelihoods ( see **Box 3** ). Some even have shifted from cereals to growing some perennial crops and trees, indicating the potential contributions of on-farm diversification for adapting to climate related shocks. Similar rainwater harvesting techniques are found to be the most popular adaptive strategies among smallholder farmers in Gladstone, South Africa (Gandure, Walker, & Botha, 2013).

**Box 3: A case of successful adaptation by a farmer (based on KII, 2013)**

Getu Ayechew, a priest in a local Degosach parish, Lasta, is a father of 6 children. He was born in the same village and recalls two devastating droughts and the resulting famine in his life time. The drought and its impact is still fresh in his memory and he resents losing two of his close relatives in the 1984 famine. He owns one hectare of farm land which he uses to grow teff. He claims his experience of the frequent droughts and crop failures has thought him a good lesson on the need to harvesting and conserving water. He first voluntered part of his farmland for a model water-harvesting scheme, and then learnt the skills to using and maintaining the well. Later on, he dug up another two water-wells in his yard and began to grow fruits and vegetables in a small patch of land. After five years of hard work, he was able to save money that he used to renting-in land from other farmers, and started breeding sheep, engage in bee-keeping and grow *gesho* (hops) as a cash crop. Now, he owns a local shop/kiosk and hopes to expand his business.

In Lasta, experiences with frequent droughts are the likely factor to triggering a relatively far more vigorous action by smallholders in terms of diversifying livelihood options. This is largely reflected in the FGDs in which participants expressed their opinion with some shared sense of urgency. This clearly indicates how past experiences with climate variability shapes the perception and the actions of people. This observation seems to agree with a recent study by D'haen et al. (2014) that find short term climatic conditions such as interruptions of rains increase participation in non-farm activities in rural Burkina Faso's moisture deficit zone.

Moreover, the findings from the two districts clearly reflect role of location. Despite both districts being major tourist destinations, the proximity to Lalibela town and access to roads and markets to bigger cities such as Dessie and Bahir Dar seem to be the decisive factors in opening-up opportunities for pursuing diversified livelihoods in Lasta district. While having tourist attractions is more or less a given condition, improving access to infrastructure is a factor amenable to policy intervention because more can be done to creating the right incentives to promote the rural non-farm economy in the district. In this regard, experiences from Central America and Mexico show that local perceptions of climate are critical in guiding policy responses on adaptation (Tucker, Eakin, & Castellanos, 2010).

Compared to Lasta, livelihood diversification in Beyeda seems to be much more restricted with little opportunities for smallholders to engage in different activities. In terms of on-farm diversification, some respondents have indicated changing crop varieties, e.g. planting early maturing barely that is highly demanded for producing malt for beer. According to key informant from the District Food Security Coordination Office, however, such practice is far less common and it is undertaken only by a handful of "model" or successful farmers. In fact, most smallholders prefer to grow eucalyptus trees for sale.

Seasonal migration to *Humera* for sesame production is also another common income earning activity pursued by smallholders. Labor migration being used as a major form of income diversification strategy can be interpreted as the lack of other income diversifying opportunities in the study villages. For instance, FGD participants have mentioned the lack of credit and infrastructure, mainly an all-weather road and market place, as obstacles to pursuing non-farm income generating activities such as trade. These results are broadly in agreement with studies conducted on household coping strategies towards drought in Ethiopia (Salih, 2001; Sharp, Devereux, & Amare, 2003).

Apart from such infrastructural problems, some cultural barriers were also mentioned hindering farmers from doing certain kinds of non-farm activities in the district. For example, some activities are considered not worth doing and a stigma is attached to people who work as weavers, potters and even towards blacksmiths that help produce tools essential for farming like hoe and plough.[18]

These cultural impediments also extend to some activities. Indeed, some discussants commented specifically on renting mule to tourists and their scouts. Having a mule has long been a status symbol in some of the remotest and mountainous villages and renting out mule to tourists used to be frowned upon by villagers as undignified way of earning income. See **Box 4.**

[18] Such attitudes used to be common among the highlanders in the past, but have significantly waned with the advent of urbanization and expansion of education.

**Box 4: Farmer's view on changing attidudes on non-farm income (based on FGD, 2013)**

" Ten years ago, my neigbours used to rebuke me for renting my mule to a local tourist scout that used to take a brief rest on their way to climbing the mountains. They used to call me 'shekalay' [one who sells everything including his pride]. With hindsight, I understand their position since living off-the land through farming has long been an established and culturally respectable trade. But now, most of my neighbours have changed their attitudes and some even rent their mules for a ridiculously lower price than I would ask for my mules" (Getenet Abate, 47, from Watti village, Beyeda).

Regarding off-farm activities that involve natural resource extraction, respondents did not volunteer to illicit information from both study areas, perhaps because such activities mostly involve cutting down trees, considered illegal. Despite this apparent lack of information however, it is reasonable to assume that some smallholders engage in activities such as charcoal-making based on some evidences observed during transient walk. Such activities are likely to aggravate environmental degradation and increase the vulnerability of smallholders.

Although surpluses generated from non-farm activities can provide farmers with income for on-farm investment, interviews with key informants revealed that it is not clear to what extent income generated from non-farm activities is reinvested into farming. It seems that households are only able to reinvest in agriculture when non-farm work is short-term and the farm work is not constrained by shortage of land, oxen or any other input. Otherwise, smallholders prefer to engage in non-farm works where they earn disposable cash for ensuring food availability at household level and smooth consumption until the next harvesting season. Key informants also disclosed that most of the earnings from non-farm activities are used to repay debt or to finance social and cultural events such as marriage and 'tezkar'– a memorial feast for a deceased family member.

In sum, diversification away from agriculture (i.e. non-farm) in the study areas seems to be seasonal and the patterns can be broadly categorized in line with Warren (2002) classifications i.e. the wage-path and the self-employment path. In any case, wage labour seems to be the dominant path for diversification. The most cited reason for not participating in many activities within the self-employment path is lack of the necessary skills, education, information, location (proximity to major urban centre) and most of all lack of financial capital.

Focus group participants suggested that households make their own assessments of the need to adapt to the changes in weather patterns based on an evaluation of their previous experiences i.e. exposure to climatic risks. This clearly demonstrates the important role of learning (from experience) which is linked to adaptability. Learning rejects the failures, secures the success and stimulates future adaptation (Collinson & Lightfoot, 2000). More than the experience, however, smallholders seem to make decisions often on the basis of available resources in relation to the pressing threats to their livelihood. For instance, asset-poor households (lacking enough land and oxen) with large family size mostly prefer to engage in sharecropping arrangements that involve contributing labour in exchange for sharing grains, to cope with the hunger season than sending their able-bodied members in search of better opportunities elsewhere. Such choices may hint to the dominance of risk-aversion in making decisions. There are also latent issues of trust and intra-household resource control especially land. For instance, land fragmentation pushes the youth to look for employment opportunities in the non-farm sector outside of their village and demand resources from their household to cover the costs of migration. However, household heads are often reluctant to invest in migration (to places as far as Saudi Arabia) not only because it is too costly and further depletes the household’s assets but also they don’t trust that the youth will make regular contributions to the household in the form of sending remittances. This situation is creating tensions and conflicts among family members. **Table 6** provides a summary of the major types of diversification strategies in the districts.

**Table 6: Major types of diversification strategies in the districts (based on FGDs)**

| Strategy | Description |
|---|---|
| Seasonal migration and casual labour | Young and able-bodied household members look for off-farm wage labour in their own village or nearest town. During off-seasons and at times of lean harvest, they migrate to neighbouring districts or regions in search of agricultural wage labour. This strategy exists in both districts but it is by far common in Lasta than in Beyeda. |
| Public works | The government's PSNP provides additional income during agricultural off-seasons. The activities are often non-farm in nature and involve water and soil conservation structures like terracing and maintaining roads. Both districts are food insecure and the PSNP's Public Work scheme provides income to the very poor households. |
| Participating in the tourism sector | The two districts are endowed with natural and historic places that attract both foreign and domestic tourists. Beyeda is located within the *Semin* mountain ranges and some farmers earn income by renting out mules and serving as scouts. Similarly, the rock-hewn churches of Lalibela from the 12th Century are located in Lasta and farmers directly or indirectly benefit from the sector by providing tour services, making and selling souvenirs etc. Compared to Lasta, farmers in Beyeda benefit less from the tourism sector. |
| On-farm diversification | In Lasta, households with irrigable land and those who have dug water wells, engage in fruits and vegetable farming or horticulture. Bee-keeping is also pursued by the youth in the district.<br>In Beyeda, planting eucalyptus trees for sale is dominating on-farm diversification strategies. |
| Participating in microenterprises | These include cobblestone making and which are undertaken by skilled persons who have received training and support from government or other NGOs. |

Source: compiled from FGDs from Lasta and Beyeda, 2013.

## 6. Conclusions

The study sought to understand the perceptions of smallholders to climate variability, change, and their adaptation responses with reference to diversification. The results show that smallholders perceived that there is climate variability and change, and identify its impacts on their livelihoods. In response to the perceived climate variability and change, farmers are already taking measures within their limited adaptive capacity.

Despite the dominance of agriculture, smallholders are able to diversify their activities and income sources. However, current patterns of diversification seem to be dominated by seasonal labour migration and off-farm strategies namely temporary agricultural wage labour, which may be insufficient as autonomous adaptation strategies to deal with the impacts of expected climate change. Non-farm diversification, which could potentially contribute to reducing vulnerability associated with climatic risks, is generally found to be limited mainly due to entry-barriers such as lack of finance and infrastructure and location.

Thus, it is reasonable to conclude that this finding can be a reflection of the high rate of vulnerability and poverty in the districts. There are subtle but important differences between the two districts that highlight the role of both climatic and non-climatic factors in adaptive capacity. Compared to Lasta, livelihood diversification in Beyeda seems to be much more restricted. This perhaps reflects the importance of location and lack of exposure to frequent climatic shocks, which is an important element of adaptive capacity. In Lasta non-farm diversification in relative terms, appears to be growing in extent and importance in recent years. Some of this increase relies on proximity to urban centre and construction and development investments made by the central government on roads and communication networks. Similarly, a host of factors such as available assets and socio-demographic considerations like household size, education and skills and cultural attitudes towards certain activities are likely to complicate the choice of diversification strategies at household level.

These factors have important implications for autonomous adaptation actions and indicate how broader socio-economic factors frame adaptation pathways at a local level, which in turn calls for complementing autonomous adaptations, by planned strategies to address these wider impediments.

Finally, some results of this study can be useful in suggesting strategies beyond small-scale irrigation schemes and rangeland management approaches that are prioritized in the country's National Adaptation Programme of Action (NAPA). In this regard, non-farm diversification strategies can be viable options to areas that do not have agricultural potential to adequately sustain livelihoods.

## References


Adger, W. N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D. R., … Wreford, A. (2009). Are there social limits to adaptation to climate change? *Climatic Change*, *93*(3-4), 335–354.

Agrawala, S., & Van Aalst, M. (2008). Adapting development cooperation to adapt to climate change. *Climate Policy*, *8*(2), 183–193. doi:10.3763/cpol.2007.0435

Ayers, J., & Forsyth, T. (2009, July). Community based adaptation to climate change [Article]. Retrieved December 4, 2012, from http://www.environmentmagazine.org/

Baas, S., & Ramasamy, S. (2008). Community based adaptation in action. *A Case Study from Bangladesh. Food and Agriculture Organization of the United Nations/Department of Agriculture Extension, Rome/Dhaka*.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331. doi:10.1016/S0306-9192(01)00014-8

Bauer, S., & Scholz, I. (Eds.). (2010). *Adaptation to Climate Change in Southern Africa: New Boundaries for Development*. Earth scan.

Below, T., Artner, A., Siebert, R., & Sieber, S. (2010). Micro-level practices to adapt to climate change for African small-scale farmers. *A Review of Selected Literature. Environment and Production Technology Division*.

Berg, B. (2001). *Qualitative Research Methods for the Social Sciences*. A Pearson Education Company.

Berg, B. L., Lune, H., & Lune, H. (2004). *Qualitative research methods for the social sciences* (Vol. 5). Pearson Boston, MA.

Bloor, M., Frankland, J., Thomas, M., & Robson, K. (2001). *Focus Groups in Social Research*. London: Sage Publications.

Campos, M., Velázquez, A., & McCall, M. (2014). Adaptation strategies to climatic variability: A case study of small-scale farmers in rural Mexico. *Land Use Policy*, *38*, 533–540. doi:10.1016/j.landusepol.2013.12.017

Cannon, T. (2014). Rural Livelihood Diversification and Adaptation to  Climate Change. In *Community-based Adaptation to Climate Change: emerging lessons*. Rugby: Practical Action Publishing.

Chambers, R. (1994). The Origins and Practice of Participatory Rural Appraisal. *World Development*, *22*(7), 953–969.

Chambwera, M., & Stage, J. (2010). *Climate change adaptation in developing countries: issues and perspectives for economic analysis*. IIED.

Cheung, W. H., Senay, G. B., & Singh, A. (2008). Trends and spatial distribution of annual and seasonal rainfall in Ethiopia. *International Journal of Climatology*, *28*(13), 1723–1734.

Christie, M., Rowe, P., Perry, C., & Chamard, J. (2000). Implementation of Realism in Case Study Research Methodology. Presented at the Annual Conference on International Council for Small Business, Brisbane.

Collinson, M., & Lightfoot, C. (2000). The future of farming systems research. *A History of Farming Systems Research, Edited by MP Collinson. FAO, Rome, Italy and CABI Publishing, Wallingford, England*, 391–419.

Conway, D. (2000). Some aspects of climate variability in the north east Ethiopian highlands-Wollo and Tigray. *Ethiopian Journal of Science*, *23*(2), 139–161.

Conway, D., Mould, C., & Bewket, W. (2004). Over one century of rainfall and temperature observations in Addis Ababa, Ethiopia. *International Journal of Climatology*, *24*(1), 77–91.

Conway, D., & Schipper, E. L. F. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global Environmental Change*, *21*(1), 227–237. doi:10.1016/j.gloenvcha.2010.07.013

Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B., Shiferaw, B., & Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? *Agriculture, Ecosystems & Environment*, *126*(1–2), 24–35.

Creswell, J. (1994). *Research Design: Qualitative and Quantitative Approaches*. London: Sage Publications.

Creswell, J. W. (2002). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. SAGE.

Davis, J. R. (2003). The rural non-farm economy, livelihoods and their diversification: Issues and options. *NRI Report*, (2753).

Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, *149*(01), 23–31. doi:10.1017/S0021859610000687

Deshmukh, D., & Lunge, H. (2013). A Study Of Temperature And Rainfall Trends In Buldana District Of Vidarbha, India. *Internal Journal of Scientific and Technology*, *2*(2), 6.

D'haen, S. A. L., Nielsen, J. Ø., & Lambin, E. F. (2014). Beyond local climate: rainfall variability as a determinant of household nonfarm activities in contemporary rural Burkina Faso. *Climate and Development*, *6*(2), 144–165.

Dinar, A. (2008). *Climate Change and Agriculture in Africa: Impact Assessment and Adaptation Strategies*. Earth scan.

Douma, A., & Hirsch, D. (2007). *Adapting to climate change: How local experiences can shape the debate* (Both ENDS Briefing Papers) (pp. 1–17). Amsterdam: Both ENDS: Environment and Development Services.

Eisenack, K. (2009). Autonomous Adaptation to Climate Change is Inefficient. Presented at the European Association of Environmental and Resource Economists, Amsterdam.

Ellis, F. (2000). *Rural Livelihoods and Diversity in Developing Countries*. Oxford University Press.

Eriksen, S., & O'Brien, K. (2007). Vulnerability, poverty and the need for sustainable adaptation measures. *Climate Policy*, *7*(4), 337–352. doi:10.1080/14693062.2007.9685660

Filho, W.(2011). *Experiences of Climate Change Adaptation in Africa*. Verlag Berlin Heidelberg: Springer.

Forsyth, T., & Evans, N. (2013). What is Autonomous Adaption? Resource Scarcity and Smallholder Agency in Thailand. *World Development*, *43*, 56–66. doi:10.1016/j.worlddev.2012.11.010

Frei, C. (2014). *Analysis of Climate and Weather Data* (pp. 1–37). Zurich: Institute for Atmospheric and Climate Science. Retrieved from www.iac.ethz.ch/edu/courses

Gandure, S., Walker, S., & Botha, J. J. (2013). Farmers' perceptions of adaptation to climate change and water stress in a South African rural community. *Environmental Development*, *5*, 39–53. doi:10.1016/j.envdev.2012.11.004

Gebrehiwot, T., & Veen, A. van der. (2013). Farm Level Adaptation to Climate Change: The Case of Farmer's in the Ethiopian Highlands. *Environmental Management*, *52*(1), 29–44. doi:10.1007/s00267-013-0039-3

Gerson, K., & Horowitz, R. (2002). Observation and interviewing: Options and choices in qualitative research. *Qualitative Research in Action*, 199–224.

Glaser, B. G., Strauss, A. L., & Strutzel, E. (1968). The discovery of grounded theory; strategies for qualitative research. *Nursing Research*, *17*(4), 364.

Gomm, R., Hammersley, M., & Foster, P. (2000). *Case Study Method: Divergent Interpretations*. London: Sage.

Gupta, J. (2002). *Our Simmering Planet: What to Do About Global Warming?*. Zed Books.

Helsel, D., & Hirsch, R. (2002). *Statistical methods in water resources, Techniques of Water-Resources Investigations of the United States Geological Survey. Book 4, Hydrologic Analysis and Interpretation. Chapter A3*.

Howe, P. D., Markowitz, E. M., Lee, T. M., Ko, C.-Y., & Leiserowitz, A. (2013). Global perceptions of local temperature change. *Nature Climate Change*, *3*(4), 352–356.

IPCC (2001) *Climate Change 2001: Synthesis Report*. Retrieved from http://www.cambridge.org/gb/knowledge/isbn/item1114842/?site_locale=en_GB

IPCC (2007) *Climate Change 2007 - Impacts, Adaptation and Vulnerability: Working Group II contribution to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)*. Cambridge University Press.

IPCC (2014) *Climate Change 2014, Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom and New York, NY, USA.: Cambridge University Press.

Jain, S. K., & Kumar, V. (2012). Trend analysis of rainfall and temperature data for India. *Current Science(Bangalore)*, *102*(1), 37–49.

Joireman, J., Barnes Truelove, H., & Duell, B. (2010). Effect of outdoor temperature, heat primes and anchoring on belief in global warming. *Journal of Environmental Psychology*, *30*(4), 358–367.

Karmeshu, N. (2012). *Trend Detection in Annual Temperature & Precipitation using the Mann Kendall Test – A Case Study to Assess Climate Change on Select States in the North-eastern United States*. University of Pennsylvania.

Kassie, B. T., Hengsdijk, H., Rötter, R., Kahiluoto, H., Asseng, S., & Ittersum, M. V. (2013). Adapting to Climate Variability and Change: Experiences from Cereal-Based Farming in the Central Rift and Kobo Valleys, Ethiopia. *Environmental Management*, *52*(5), 1115–1131. doi:10.1007/s00267-013-0145-2

Kelly, P. M., & Adger, W. N. (2000). Theory and practice in assessing vulnerability to climate change and Facilitating adaptation. *Climatic Change*, *47*(4), 325–352.

Kemausuor, F., Dwamena, E., Bart-Plange, A., & Kyei-Baffour, N. (2011). Farmers perception of climate change in the Ejura-Sekyedumase district of Ghana. *ARPN Journal of Agricultural and Biological Science*, *6*(19), 26–37.

Lanjouw, J. O., & Lanjouw, P. (2001). The rural non-farm sector: issues and evidence from developing countries. *Agricultural Economics*, *26*(1), 1–23.

Leary, N., Baethgen, W., Barros, V., Burton, I., Canziani, O., Downing, T. E., … Wandiga, S. (2006). *A Plan of Action to Support Climate Change Adaptation through Scientific Capacity, Knowledge and Research* (AIACC Working Paper). Washington: Assessment of Impacts and Adaptations to Climate Change ( AIACC). Retrieved from http://www.aiaccproject.org/working_papers/Working%20Papers/AIACC_WP23_Leary.pdf

Legesse, B., Ayele, Y., & Bewket, W. (2013). Smallholder Farmers' Perceptions and Adaptation to Climate Variability and Climate Change in Doba District, West Hararghe, Ethiopia. *Asian Journal of Empirical Research*, *3*(3), 251–265.

Lim, B., Spanger-Siegfried, E., Burton, I., Malone, E., & Huq, S. (2005). *Adaptation policy frameworks for climate change: developing strategies, policies, and measures*. Cambridge University Press Cambridge.

Li, Y., Johnson, E. J., & Zaval, L. (2011). Local warming daily temperature change influences belief in global warming. *Psychological Science*.

Longobardi, A., & Villani, P. (2010). Trend analysis of annual and seasonal rainfall time series in the Mediterranean area. *International Journal of Climatology*, *30*(10), 1538–1546.

Macchi, M., Oviedo, G., Gotheil, S., Cross, K., Boedhihartono, A., Wolfangel, C., & Howell, M. (2008). *Indigenous and Traditional Peoples and Climate Change*. Gland, Switzerland: IUCN.

Maddison, D. (2007). *The Perception Of And Adaptation To Climate Change In Africa*. The World Bank. Retrieved from http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-4308

Mann, H. (1945). Non parametric tests again trend. *Econometrica*, *13*, 245–259.

Maplecroft. (2015). *Climate Change Vulnerability Index 2015*. United Kingdom: Maplecroft. Retrieved March 3, 2015 from www.maplecroft.com

Marshall, M. (1996). The key informant techniques. *Family Practice*, *13*(1), 92–97.

May, T. (2002). *Qualitative Research in Action*. London: Sage Publications.

McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J., & White, K. S. (2001). *Climate Change 2001: Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Mendelsohn, R. O., & Dinar, A. (2009). *Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional Effects*. Edward Elgar Publishing.

Mertz, O., Mbow, C., Reenberg, A., & Diouf, A. (2009). Farmers' Perceptions of Climate Change and Agricultural Adaptation Strategies in Rural Sahel. *Environmental Management*, *43*(5), 804–816. doi:10.1007/s00267-008-9197-0

Meze-Hausken, E. (2004). Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate Research*, *27*, 19–31.

O'Connor, R. E., Bord, R. J., & Fisher, A. (1999). Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk Analysis*, *19*(3), 461–471.

Patton, M. Q. (2003). Qualitative evaluation checklist. *Evaluation Checklists Project*.

Patton, M. Q. (2005). *Qualitative research*. Wiley Online Library.

Perret, S. R., & Stevens, J. B. (2006). Socio-economic reasons for the low adoption of water conservation technologies by smallholder farmers in southern Africa: a review of the literature. *Development Southern Africa*, *23*(4), 461–476.

Pielke, R., Prins, G., Rayner, S., & Sarewitz, D. (2007). Climate change 2007: Lifting the taboo on adaptation. *Nature*, *445*(7128), 597–598. doi:10.1038/445597a

Rao, V., & Woolcock, M. (2003). *Integrating Qualitative and Quantitative Approaches in Program Evaluation*.

Reardon, T., Stamoulis, K., Balisacan, A., Cruz, M., Berdegué, J., & Banks, B. (1998). Rural non-farm income in developing countries. *The State of Food and Agriculture*, *1998*, 283–356.

Río, S. del, Herrero, L., Fraile, R., & Penas, A. (2011). Spatial distribution of recent rainfall trends in Spain (1961–2006). *International Journal of Climatology*, *31*(5), 656–667.

Ritchie, J., Lewis, J., Nicholls, C. M., & Ormston, R. (2013). *Qualitative research practice: A guide for social science students and researchers*. Sage.

Robson, C. (1993). Real world research: A resource for social scientists and practitioners-researchers. *Black, Well Publishers Ltd., Oxford*.

Rockstrom, J. (2000). Water resources management in smallholder farms in Eastern and Southern Africa: an overview. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, *25*(3), 275–283.

Roncoli, C., Okoba, B., Gathaara, V., Ngugi, J., & Nganga, T. (2010). Adaptation to climate change for smallholder agriculture in Kenya: community-based perspectives from five districts. *University of Georgia Report to the World Bank for the Project "Adaptation to Climate Change of Smallholder Agriculture in Kenya," June*.

Salih, M. M. (2001). Climate Change and Local Vulnerability: Exploring the Linkages. In *Local Environmental Change and Society in Africa* (pp. 203–220). Springer.

Seleshi, Y., & Zanke, U. (2004). Recent changes in rainfall and rainy days in Ethiopia. *International Journal of Climatology*, *24*(8), 973–983.

Selvaraju, R., Subbiah, A., Baas, S., & Juergens, I. (2006). Livelihood adaptation to climate variability and change in drought-prone areas of Bangladesh: Developing institutions and options.

Seo, S. N., & Mendelsohn, R. (2007). *Climate change adaptation in Africa : a microeconomic analysis of livestock choice*. The World Bank. Retrieved from http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-4277

Sharp, K., Devereux, S., & Amare, Y. (2003). *Destitution in Ethiopia's Northeastern highlands (Amhara National Regional State)*. Institute of Development Studies at the University of Sussex.

Shrestha, A. B., Wake, C. P., Mayewski, P. A., & Dibb, J. E. (1999). Maximum temperature trends in the Himalaya and its vicinity: An analysis based on temperature records from Nepal for the period 1971-94. *Journal of Climate*, *12*(9), 2775–2786.

Silverman, D. (2001). *Interpreting Qualitative Data: Methods for Analysing Talk Text, and Interaction*. London: SAGE Publications.

Simoons, F. J. (1960). Snow in Ethiopia: A Review of the Evidence. *Geographical Review*, *50*(3), 402–411. doi:10.2307/212283

Smit, B., McNabb, D., & Smithers, J. (1996). Agricultural adaptation to climatic variation. *Climatic Change*, *33*(1), 7–29. doi:10.1007/BF00140511

Stafford, J., Wendler, G., & Curtis, J. (2000). Temperature and precipitation of Alaska: 50 year trend analysis. *Theoretical and Applied Climatology*, *67*(1-2), 33–44.

Stake, R. E. (1995). *The Art of Case Study Research*. Sage.

Stern, N. (2007). *The economics of climate change: the Stern review*. Cambridge University press.

Stringer, L. C., Mkwambisi, D. D., Dougill, A. J., & Dyer, J. C. (2010). Adaptation to climate change and desertification: Perspectives from national policy and autonomous practice in Malawi. *Climate and Development*, *2*(2), 145–160.

Swai, O., Mbwambo, J., & Magayane, F. (2012). Gender and perception on climate change in Bahi and Kondoa Districts, Dodoma Region, Tanzania. *Journal of African Studies and Development*, *4*(9), 218–231. doi:10.5897/JASD12.038

Tacoli, C. (1998). Rural-urban interactions; a guide to the literature. *Environment and Urbanization*, *10*, 147–166.

Thomas, D. (2006). A general inductive approach for analysing qualitative evaluation data. *American Journal of Evaluation*, *27*(2), 237–246.

Tucker, C. M., Eakin, H., & Castellanos, E. J. (2010). Perceptions of risk and adaptation: coffee producers, market shocks, and extreme weather in Central America and Mexico. *Global Environmental Change*, *20*(1), 23–32.

UN Women Watch. (2009). *Women, Gender Equality and Climate Change* (Fact Sheet) (p. 11). The UN Internet Gateway on Gender Equality and Empowerment of Women. Retrieved from http://www.un.org/womenwatch/feature/climate_change/

Van Aalst, M. K., Cannon, T., & Burton, I. (2008). Community level adaptation to climate change: The potential role of participatory community risk assessment. *Global Environmental Change*, *18*(1), 165–179. doi:10.1016/j.gloenvcha.2007.06.002

Warren, P. (2002). Livelihoods diversification and enterprise development. *An Initial Exploration of Concepts and Issues. Livelihood Support Program (LSP) Working Paper*, *4*.

Weber, E. U. (2006). Experience-based and description-based perceptions of long-term risk: Why global warming does not scare us (yet). *Climatic Change*, *77*(1-2), 103–120.

Wigley, T. M. ., & Jones, P. . (1981). Detecting CO2-induced climate change. *Nature*, *292*, 205–208.

Wooldridge, J. (2008). *Introductory Econometrics: A Modern Approach*. Cengage Learning.

Yadav, S. S., Redden, R., Hatfield, J. L., Lotze-Campen, H., & Hall, A. J. W. (2011). *Crop Adaptation to Climate Change*. John Wiley & Sons.

Yin, R. (1994). *Case Study Research: Design and Methods*. Newbury Park: Sage.

Yue, S., & Hashino, M. (2003). Temperature trends in Japan: 1900–1996. *Theoretical and Applied Climatology*, *75*(1-2), 15–27.

Zhang, X., Vincent, L. ., Hogg, W. ., & Niitsoo, A. (2000). Temperature and Precipitation Trends in Canada During the 20th Century. *Atmosphere-Ocean*, *38*(3), 395–429.

## Annex

**Table A: Statistical summary of rainfall data in the two districts**

| Station | Record period | Season | MR (mm) | St.Dev | CV (%) | Trend |
|---|---|---|---|---|---|---|
| Debark | 2000–2011 | Belg | 116.3 | 62.6 | 53.9 | 0.27* |
| | | Kiremt | 933.7 | 129.5 | 13.8 | 0.01 |
| | | Annual | 1098.1 | 158.1 | 14.4 | 0.02 |
| Lalibela | 1989–2011 | Belg | 122.0 | 74.6 | 61.0 | 0.12 |
| | | Kiremet | 547.7 | 188.9 | 34.5 | 0.04 |
| | | Annual | 713.5 | 187.5 | 26.3 | 0.00 |

Source: computed from meteorological data

*Notes:*

*Trends statistically significant at $p<0.10$.
**MR** = Mean Rainfall
**St. Dev**= Standard deviation
**CV**= Coefficient of variation (St. Dev divided by the mean)
Trend is indicated by coefficient of determination ($R^2$)

**Table B: Major Livelihood shocks in Lasta as re-constructed from the Participatory historical time line exercise done with FGD participants.**

| No. | Year | Major Shocks and events |
|---|---|---|
| 1 | 1966 | Drought, epidemics, famine |
| 2 | 1974 | Pest, change in land tenure |
| 3 | 1980 | Pest |
| 4 | 1984 | Drought, major famine |
| 5 | 1987/88 | Drought |
| 6 | 1990 | Change in regime |
| 7 | 1998/99 | Malaria epidemics |
| 8 | 2002 | Drought |
| 9 | 2005 | Drought |
| 10 | 2011/12 | Floods, hailstones |
| 11 | 2013 | Heat wave |

**Table C. Serial correlation and heteroskedasticity tests**

1. **Mean maximum temperature in Beyeda**

Dickey-Fuller test for unit root Number of obs. = 9

| | Test Statistic | ---------- Interpolated Dickey-Fuller --------- 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | -0.753 | -3.750 | -3.000 | -2.630 |

MacKinnon approximate p-value for Z(t) = 0.8324

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of Max_temp

chi2(1) = 1.17
Prob > chi2 = 0.2789

2. **Mean Maximum temperature in Lasta**

Dickey-Fuller test for unit root Number of obs. = 19

| | Test Statistic | ---------- Interpolated Dickey-Fuller --------- 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Z(t) | 0.164 | -3.750 | -3.000 | -2.630 |

MacKinnon approximate p-value for Z(t) = 0.9702

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of Max_temp

chi2(1) = 0.30
Prob > chi2 = 0.5815

**Climate Data Trend analysis: The Mann–Kandall (M-K) trend test**

The test Mann-Kandall (M-K) trend test was first developed by Mann (1945) who formulated "a non-parametric test for randomness against time which involves a particular application of Kandall's test for correlation" (Longobardi & Villani, 2010:5).

This test reduces the temperature records to ranks rather than magnitudes and remove the influence of outliers (Cheung et al., 2008). The main advantage of the M-K test is that it does not require the data to be normally distributed (Karmeshu, 2012).

The results from the M-K tests also support the results from the simple linear regression model, which is that there is a statistically significant upward trend in the mean minimum temperature over Ethiopia during the period 1960-2006.

Let X1, X2, . . .,Xn be a sequence of measurements over time, the M-K tests the null hypothesis ($H_0$) that time series values are independent and identically distributed against the alternative hypothesis ($H_1$), which states that the data follow a monotonic trend over time (Longobardi & Villani, 2010; Frei, 2014) . Under $H_0$, the M-K test statistic (S) is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(X_j - X_i\right) \qquad (1)$$

$$\text{where} \quad sign(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \qquad (2)$$

For a large sample ( $n \geq 8$) and if the residuals are mutually independent ( see Frei, 2014), the $S$ statistic is approximately normally distributed, with zero mean and variance as follows:

$$\sigma^2 = \frac{n(n-1)(2n+5)}{18} \tag{3}$$

Accordingly, the standardized *Z* statistics can be compared to normal distribution:

$$\boldsymbol{Z = \begin{cases} \dfrac{S-1}{\sigma} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{S+1}{\sigma} & if\ S < 0 \end{cases}} \tag{4}$$

The null hypothesis ($H_0$) that time series values are independent or there is no trend will be rejected when the *Z* value is greater than the critical value $Z\alpha$ at the level of significance ($\alpha$ =0.05) (Longobardi & Villani, 2010).

**Mann-Kendall Trend Test Results**

Mann-Kendall trend test / Two-tailed test (Mean maximum temp. Lasta):

| | |
|---|---|
| Kendall's tau | 0.333 |
| S | 70.00 |
| Var(S) | 0.000 |
| p-value (Two-tailed) | 0.037 |
| alpha | 0.05 |

The p-value is computed using an exact method.
Test interpretation:

H0: There is no trend in the series
Ha: There is a trend in the series
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 3.66%.

Mann-Kendall trend test / Two-tailed test (mean max. temp. in Beyeda):

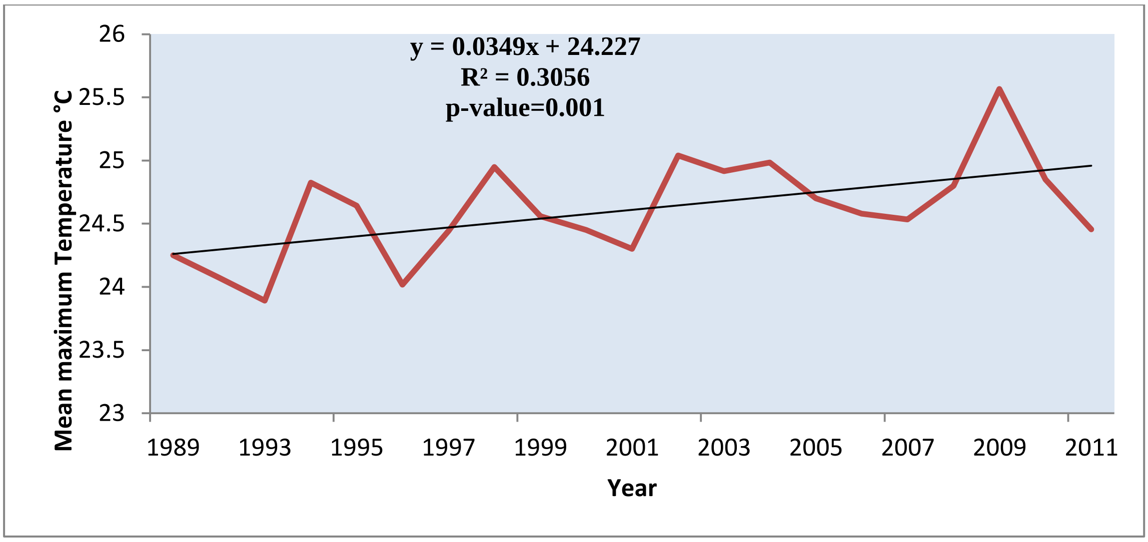
| | |
|---|---|
| Kendall's tau | 0.600 |
| S | 27.00 |
| Var(S) | 0.000 |
| p-value (Two-tailed) | 0.017 |
| alpha | 0.05 |

The p-value is computed using an exact method.

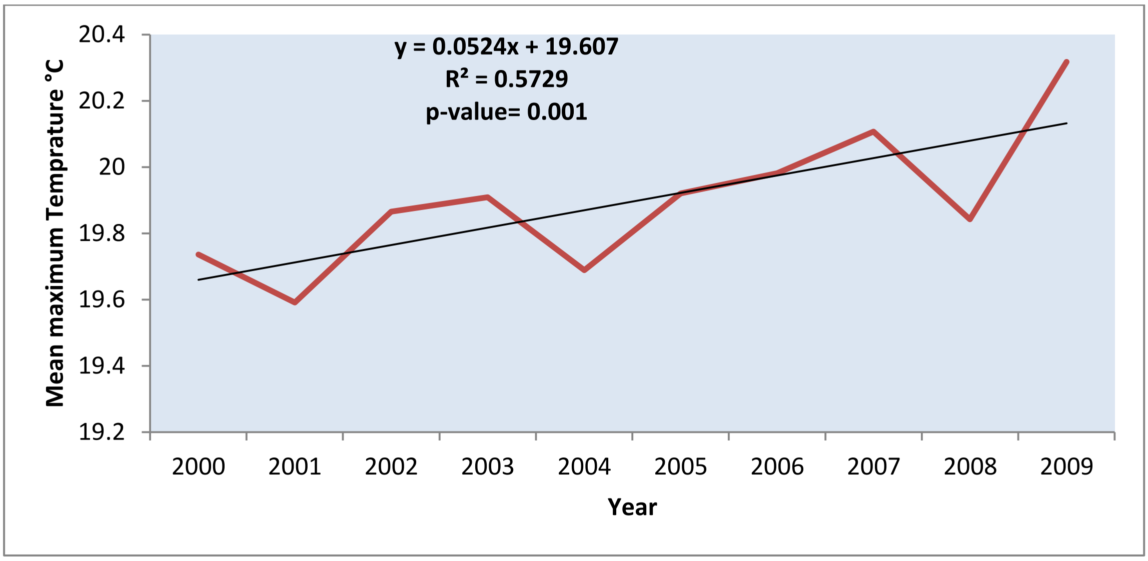
Test interpretation:
As the computed p-value is lower than the significance level alpha=0.05,
one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 1.67%.

## Trends in mean maximum temperature

### Figure A: Mean Maximum Temperature in Lasta, 1989–2011.




### Figure B: Mean Maximum Temperature in Beyeda, 2000–2009.




*Note*:
Maximum temperature in 2010 has missing observations for four months. Hence, the trend for maximum temperature in Beyeda is computed on data from 2000-2009.

**Table D: Household wealth status based on local perception about wealth in Lasta district**

| Wealth Group | Profile of wealth group | Estimated % of households |
|---|---|---|
| Rich | Own more than 2 ha of land ( including irrigable land), can produce or able to buy enough grains to feed all household members; can meet social and religious obligations (fists, weddings, funerals, religious festivities, holidays etc…) throughout the year without taking loan; having well-constructed large house(s) covered with corrugated iron roofs and sometimes made from stone and cement; own one or two mule, more than 2 donkeys, more than three oxen, more than two cows, more than 30 sheep and goats. | Less than 1 in 10 (10%) of households in the two villages. |
| Medium | Own 1 – 2 ha of land, can produce or able to buy enough grain to feed the household having average-sized house covered with corrugated iron roof*, own one mule, own one or two oxen, one cow, up to 20 sheep and goats. | Between 2–3 out of 10 households (10–30 %) |
| Poor | Own less than 1 ha of land, can't produce enough to feed the household all year round, having one or no ox, having no mule, no donkey, and owing less than 10 sheep and goats. | Between 4– 6 out of 10 households (40-60 %) |
| Very poor | A household owning 0.25 ha of land or having no farm land of its own, mainly depend on wage labour (including participating in the public works of the PSNP); having poorly constructed house; and depend on borrowing money from their friends and relatives to make ends meet. | About 4 in 10 households (40%) |

Source: Wealth ranking exercise by community members from FGDs, 2013

*Note:*

Corrugated iron roof is mostly used as an indicator of wealth even in official statistical reports by CSA. However, most households in the studied villages have houses with corrugated iron roofs. Traditionally, houses (tukuls) are covered with roofs made of grass (thatched roof). However, as indicated by respondents, the type of grass that is suited for this purpose is hard to come by perhaps indicating environmental degradation and change in the villages and people are resorted to using corrugated iron. As a result, the size of the house and/or materials used such as cement or brick can serve as a better indicator of wealth.

### Table E: Activity Calendar in Lasta district (based on PRA, 2013)

| **Agricultural Activities** | **Planting Belg Crops** | | | | **Harvesting for Belg crops** | **Preparing land for planting Meher crops** | | | **1st & 2nd ploughing for Belg Crops** | | **Harvesting & Threshing** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sale of Calf or Colt | | | | | | | | | | | | |
| Sale of Shoats | | | | | | | | | | | | |
| Collection of Wild fruits/vegetables | | | | | | | | | | | | |
| Renting labour | | | | | | | Weeding | Weeding | | | Harvesting & Threshing | |
| Sale of grains | | | | | | | | | | | | |
| Pulse and grain purchase | | | | | | | | | | | | |
| Sale of woifen/Heifer/Ox | | | | | | | | | | | | |
| Animal Purchase | | | | | | | | | | | | |
| House Maintenance | | | | | | | | | | | | |
| Soil & water conservation | | | | | | | | | | | | |
| | **Jan.** | **Feb.** | **Mar.** | **April** | **May.** | **June** | **July** | **Aug.** | **Sep.** | **Oct.** | **Nov.** | **Dec.** |

**Key**

- Rich
- Medium
- Poor
- V. Poor

***Notes***:

June, July, and August belong to the main rainy season (kiremet)

March, April, and May belong to the short rainy season(Belg)

**Semi-Structured interview checklist with key-informant smallholder farmers**

Identification of key informants:

Name ___________________________________

Age ___________

Education level___________

Family size____________ Primary occupation ________________

**Part I. Perceptions on climate variability and change**

1. What does climate variability and climate change mean to you?

(The interviewer needs to translate these terms into Amharic focusing mainly on time-frame differences)

*(Probe, let the interviewee explain what they understand using their own terms for climate variability and change and ask him/her to tell you more about the nature of these changes.*

2. Have you experienced any changes in your local climate in the last 30 years?

*(Probe: If the answer is yes, ask them to tell you their experiences and indicators of changes)*

*Prompt: How do they perceive changes in the local temperature, rainfall and extreme events such as drought and flooding in their village in terms of their coverage/extent, seasonality, frequency and duration?)*

**Part II. The effect of climate variability and change**

1. Tell me about your experiences of the effects of climate variability and change

*(Probe: make sure that the interviewee discusses how the change affected their livelihoods in different sectors/activities)*

2. What are the biggest climate-related hazards you faced?

3. How are these hazards likely to change over time as a result of climate change?

4. How do you withstand the effects of climate variability and change?

**Part III. Livelihood Diversification**

Perception of livelihood systems, including livelihoods, economic, socio-cultural and political systems and the constraints, vulnerabilities, marginalization, and risks

1. What are the major livelihood activities in your village?
2. Do you diversify your income sources? Does this include non-agricultural income generating activities?
3. In your opinion, are there enough non-farm income generating activities in your village?
4. What are the common non-farm activities that people in your village engage in?
5. Do you think these types of activities help you to withstand the effects of climate-change related shocks?
6. What do you think are the major barriers/ constraints to engage in non-farm activities in your village?

**Focus Group Discussion Guide**

Date and Location ___________________

FGD Team___________________________

1. **Purpose of the FGD (5 minutes)**

The objective of this Focus Group Discussion is to get information as part of a PhD research project titled 'Responding to climate change: Social Protection and Livelihood Diversification in Rural Ethiopia' The FGD mainly serve to determine farmers' perceptions and knowledge on climate variability, change and its impact on their livelihoods. It will also help as an input to explore the link between the Productive Safety Net Programme (PSNP) and livelihood diversification of smallholder households.

1. **Introduction of participants and facilitators (5-10 minutes)**
2. **Discussion Themes**

1. Farmers' perception on climate variability and climate change in their locality (15 minutes)

*Guide questions:*

- *Do you think that the climatic has shown a marked change over the last 20 years?*
- *Is there a noticeable change in average temperature over the last two decades?*
- *What about the change in average rainfall?*
- *How often do major climatic hazards occur in their area?*

2. Farmers' assessment of the risks of climate variability and change on their livelihoods(10 minutes)

*Guide question:*

- *How do you describe the risks associated with these changes on your assets, income and productivity?*

3. Farmers' perception of their likelihood of effectively managing these risks (15 minutes)

*Guide question:*

- *How do you cope with climatic extremes in your area?*

4. Farmers' assessment of how the PSNP helps them to effectively manage climate related risks (10 minutes)
5. Ways through which farmers adapt to climate variability and change (autonomous adaptation) (15 minutes)

*Guide questions*:

- *What are the major local varieties of crops grown in this area?*
- *How many varieties of do you grow? How long have you been growing those varieties?*
- *Do you think that crop diversity helps you to adapt to climate variability and change?*
- *How does the government PSNP help you to increase farm or crop diversification?*
- *What are the major non-farm activities that you're engaged in?*
- *Do you think that non-farm diversification helps you to adapt to climate variability and change?*
- *How does the government PSNP help you to increase farm or crop diversification?*

**3. Summary of Discussion points (5 minutes)**

**4. Closing Remarks (5 minutes)**

**Semi-Structured key-informant interview checklist with district Agriculture Development and Food Security and Disaster Prevention and Preparedness experts**

Identification of key informants:

Name: ________________________________

Position: _________________________________

Expertise (education and training) ________________

Experience in this position ______________________

**I. Nature of Climate-induced Shocks and Vulnerabilities**

What are the major sources of livelihood shocks in the district related to climate variability and change?

*(Probe, would you please tell us more about the nature of climate induced hazards in the district, in terms of their Coverage/extent, seasonality, frequency and duration?*)

1. The area of land usually affected by drought and floods in the district as measured in terms of hectare or other local units of measurements.
2. What are the drought and flood seasons?
3. How often do major droughts and floods occur in this district?
4. How severe is the effects of these hazards on local people and their livelihoods*?*
5. What types of households are most vulnerable to these climatic hazards?
6. What are local peoples' main coping mechanisms? In your opinion, which of these mechanisms seem effective and sustainable?
7. For what supports communities most depend on your office?
8. How do you assess the contribution of the office in terms of promoting the resilience of rural households towards climate-related disasters in the district? (In other words, do you have any programs or projects that deal with increasing the capacity of households to better withstand the effects?)
9. Are there any other interventions by NGOs in this area with regards to promoting resilience of rural households in the face of climatic disasters?

**II. On livelihood Diversification**

Perception of livelihood systems, including livelihoods, economic, socio-cultural and political systems and the constraints, vulnerabilities, marginalization, and risks.

2. What is the major livelihood activity that smallholders engage in your district?
3. Is non-farm diversification strategies exist in the district?
4. What are the common non-farm activities that people engage in?
5. What are the major barriers to households in non-farm diversification strategies?
6. What is your office's role in providing services to households to engage in non-farm activities( credit, land provision and licensing …)

## Essay 2

# Analysis of Household Income Diversification into Rural Non-Farm activities in Ethiopia: What Determines Participation and Returns? *


### Abstract

Diversification has long been viewed as a risk minimization strategy in the face of increasing climatic and economic risks in developing countries. The paper makes a conceptual distinction between non-farm and off-farm income and uses both the number of activities and income to measure non-farm diversification. In its first part, the paper examines the determinants of non-farm activity and income diversification in rural Ethiopia for a panel of 1306 households from the recent two rounds over the period 2004–2009 of the Ethiopian Rural Household Survey (ERHS) using count data and limited dependent variable models. In the second part, it includes data from earlier two periods of the ERHS for the periods of 1994 and 1997 and uses fixed and random effects models to control for unobserved characteristics. The results suggest that consumption, and livestock holdings variables are likely to increase non-farm income diversification. This may reflect that non-farm diversification is pursued by wealthier households. Coupled with instrumental variable estimations to ascertain the direction of causality, these findings lend support to the argument that the main motivation for increasing non-farm income is accumulation. This situation in turn may reflect the existence of entry-barriers and poverty traps pervasive in rural Ethiopia. Some measures that enable poor households to benefit from the rural non-farm economy, such as promoting access to credit, electricity, and opportunities for education and employment, may lift these barriers.



**Keywords**: Non-farm income diversification, count-data models, fixed and random effects, rural Ethiopia

JEL codes: Q12 J24 R20 D19 C26



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## 1. Introduction

Diversification involves the maintenance and continuous alteration of a highly-varied range of activities and occupations to minimize household income variability, reduce the adverse impacts of seasonality and provide employment / additional income (Ellis, 2000; Barrett et al., 2001; Lanjouw & Lanjouw, 2001; Davis & Bezemer, 2004; Haggblade et al., 2010). Despite such benefits, diversification can also have negative sides depending on the motivation behind it (Hart, 1994). For instance, certain types of diversification may provide short-term security but trap households in low-return activities that make poverty persistent (such as poorly-paid piecework that leads to the neglect of farm production) or can degrade the natural-resource base (such as unsustainable charcoal production) (Barrett, Reardon, & Webb, 2001; Ellis & Freeman, 2005). Therefore, there is an important conceptual distinction among two types of diversification: off-farm and non-farm strategies (see also Weldegebriel and Prowse, 2013).

Activities of the non-farm economy are usually categorized into three major sectors: trade, manufacturing and service. This paper follows Ellis (2000) and categorizes activities not directly related to agricultural production as non-farm, including non-agricultural wage or salaried employment and self-employment, rent income, transfers, and remittances. It excludes agricultural wage or exchange labour and natural resource extraction (mainly charcoal making) as off-farm income. The focus of this paper is on non-farm diversification and on the contribution it can make in transforming the rural economy (Reardon 1997; Lanjouw and Lanjouw, 2001; Haggblade et al. 2010).

Most analyses on diversification in Ethiopia focus on poverty and inequality and have shown the importance of non-farm income for rural livelihoods (Tegenge, 2000; Woldehanna &

Oskam, 2001; Sosina & Barrett, 2012; Sosina, Barrett & Holden, 2012; Porter, 2012). But only few studies dealt with the determinants of diversification strategies (Tegenge, 2000; Demisse & Workinhe, 2004; Lemi, 2006; 2010). These studies however, used sectoral categorization and mostly included off-farm activities as part of the Non-Farm Rural Economy (NFRE).[19] This paper complements these few studies and addresses the lack of empirical evidence especially on non-farm diversification motives in three ways. First, following Ellis (1998; 2000) and Barrett, Reardon, & Webb (2001), it makes use of a rigorous operational definition that clearly distinguishes between non-farm and off-farm activities. This distinction is important for analyzing the implications of livelihood strategies on risk management, asset accumulation, natural resource management and climate adaptation as will be discussed in the next paragraphs. Second, the paper uses four rounds of ERHS surveys and applies various econometric models (tobit and double-hurdle) as well as Fixed and Random effects estimations to control for unobserved household's characteristics that may correlate with household diversification decisions. Third, it implements an instrumental variable approach to check the direction of causality between non-farm diversification and significant variables to find out the dominant motive for non-farm diversifications i.e. push/distress or pull/accumulation.

The paper is organized into two major parts on the basis of the methods of analysis and data employed. The first part uses count data and limited dependent variable models to examine the determinants of non-farm activity and income diversification for a data pooled from the recent two rounds of the Ethiopian Rural Household Survey (ERHS) over the period 2004–

[19] Lanjouw & Lanjouw (2001) define the rural nonfarm economy (RNFE) as a set of economic activities in rural areas excluding activities related to the production of primary agricultural products. It mainly incorporates activities such as food processing, small businesses, income from interests, dividends, rents, remittances, and social transfers.

2009. The second part uses data from four rounds of the same survey over the period 1994–2009 and uses panel data estimations of fixed, random effects and instrumental variable regression.

The paper proceeds as follows. Section 2 provides a brief overview of definitional concerns related to non-farm diversification and establish a working definition of non-farm income that will be used throughout the paper. Section 3 discusses the theoretical framework. Section 4 gives a survey of the literature. Section 5 describes the data and econometric approach used in the first part of the paper. Section 6 presents and discusses the empirical findings of the first and second parts and Section 7 concludes with some policy implications.

## 2. Rural livelihood diversification: Definition and Measurement

The literature offers several definitions of diversification. Some view diversification referring to an increase in multiple activities (pluri-activity) irrespective of the sector (Meert et al., 2005). Others focus on sectoral change and take a shift away from traditional/agricultural sector to non-traditional activities in rural or urban areas as diversification (Start, 2001).

Perhaps by far the most widely used definition of livelihood diversification that comprises both ‘multiplicity’ of activities and sectoral transformation is the one used by Ellis (2000:15) which defines it as “the process by which rural households construct an increasingly diverse portfolio of activities and assets in order to survive and to improve their livelihood.”

Diversification also refers to an increase in the sources of income and the balance between different sources (Ellis, 2000; Minot, 2006). Accordingly, a household with one source of income would be less diversified than a household with two sources of income, and a household with two income sources, each contributing equal share of the total would be more diversified than a household with one source accounting for 90 percent of its income and the second only for 10 percent (Joshi, 2002 as cited in Minot, 2006:5).

The term income diversification is mostly used in connection with livelihood diversification for ease of analysis and interpretation. However, Ellis (1998) makes a distinction between the two and defines income diversification as the composition of household income at a given point in time while livelihood diversification is considered as an active social process involving engagement in increasingly complex portfolio of activities overtime.

According to Barrett et al. (2001), diversification can be measured by using activities, income and assets. Households use both productive assets, mainly land and human capital, and unproductive assets such as household items and property and engage in various activities to generate income. Thus, assets, activities and income can serve as complementary indicators of diversification (Barrett et al., 2001; Senadza, 2012).

The valuation of assets is difficult especially in the African context due to the lack of secondary asset markets and variability of returns to assets because of asset fixity.[20]Activities on the other hand, despite being useful in identifying diversification choices, are difficult to value and lack direct theoretical relevance. For instance, Ellis (2004) observes that using activities as a diversification measure can be misleading as the poor may report higher degrees of diversity based on the number of activities than their better-off counterparts and yet the poor diversify in the form of off-farm casual labour, while the better off are engaged in non-farm businesses. Therefore, in most studies of livelihood diversification, income is

[20] Refers to the problem of agricultural inputs such as land unable to adjust to changing market signals or price changes in the agricultural sector of less developed countries (see Colman & Young, 1997).

used as a measure of diversification since it provides a clear interpretation of the welfare outcome (Barrett et al., 2001).Similarly, in this paper, income is employed as an indicator of the level of livelihood diversification of households since livelihoods and income are intimately linked as the composition and level of household's income at a given point in time is the most direct and measurable outcome of the livelihood process.

Barrett et al. (2001) propose using a three-way classification of income earned from different activities for the purposes of analyzing diversification. These are sectoral, functional and spatial.

1. Sectoral classification is the most basic classification that follows the national accounting systems and makes distinctions among primary, secondary and tertiary economic sectors. Primary sector comprises agriculture, mining and related extractive activities. Secondary sector mainly refers to manufacturing activities and tertiary sector constitutes a range of service provision activities. If one follows this classification, all activities and income earned outside agriculture are considered as non-farm income. A problem with this approach is that one can make the mistake of classifying wage-employment within the agricultural sector as farm income while in reality, it should be classified as off-farm (away from one's own farm) income.
2. Functional classification concerns with making a distinction between waged or salaried employment vs. self-employment. According to Barrett et al. (2001) such classification can be depicted in a continuum with distinctions made between skilled and unskilled employment and most skilled labour participating in non-farm activities.
3. Spatial classification. This can be of two types– local and distant or away from home (migratory). The local can be subdivided into two categories: On-farm and off-farm i.e. away-from one's own land. This classification also includes non-farm activities in the off-

farm category. The migratory type can also be two sub-types– domestic and international (cross-border) migration.

Ellis (1998) distinguishes three different categories of income sources– farm, off-farm and non-farm. Farm income source include income earned from crop and livestock production, including own consumption and sales. Off-farm income mainly refers to wage or exchange of labour in cash or in-kind away from one's own land within agriculture. It also includes some self-employment in natural resource extraction activities. On-farm income broadly comprises of the following non-agricultural income sources– rural non-farm wage employment, self-employment (own business), property income (from rents) and remittances and transfers.

This paper adopts the sectoral classification of Barrett et al. (2001) alongside Ellis's categories of farm, off-farm and non-farm income sources and defines non-farm income as income derived from rural non-agricultural activities including waged or salaried employment[21], self-employment[22], rents and remittances. In addition to income, activities are used to cross-check on the inferences obtained from income as recommended by Barrett et al. (2001).

[21] Nonfarm wage income is composed of income earned from the following sources as reported in the data: Professional (Teacher, government worker), skilled labourer (Builder, Thatcher), Soldier, driver/Mechanic, unskilled non-farm worker, domestic servant, and guard.

[22] Nonfarm self-employment largely constitutes income earned from own-business activities such as Weaving/spinning, milling, handicraft, including pottery, trade in grain/general trade, income from services such as traditional healer/religious teacher, transport (by pack animal), selling *injera* and *wett* (stew), hairdressing and tailoring. It also includes the making and selling of local drinks, carrying goads, builder (masonry), making roof for houses, rock splitting, and fruit and vegetable vending.

## 3. Theoretical Model/ Framework

There are different theoretical models that apply to the analysis of non-farm activities. One such model is the theory of agricultural households, which is based on the works of economists in the 1960s such as Mellor (1963) and Sen (1966). The theory views a rural household having a dual role as a production and a consumption unit. In this case, the rural household or individual's decision to supply labour to the rural non-farm sector can be conceptualized as a specific application of the class of behavioural models of factor supply in general, and labour in particular (Colman & Young, 1997; Reardon et al., 2007). Economists model both the labour supply and capital investment in a particular non-farm activity, as a function of incentives and constraints. In other words, "the household is assumed to want to maximize earnings subject to constraints imposed by its limited resources and in trade-off with its desire to minimize risk" (Reardon et al., 2007:137).

Incentives include the level and variability of prices and wages in both farm and non-farm activities, variation in relative risks involved in pursuing activities such as climatic, market, or other risks. Constraints are related to the capacity of a household to diversify into non-farm activities including individual and household characteristics: age, gender, education household size, assets and access to credit (Barrett, Reardon, & Webb, 2001; Reardon et al., 2007). Incentives can be shaped by capacity variables. For instance, prices may differ among rural households due to heterogeneous access to markets, differing human capital and asset endowments.

According to Reardon et al. (2007:138), the set of incentives and constrains is assumed to create "paradoxes at the meso and micro-level". At the meso-level and in resource-poor areas, farmers have higher incentives to participate in non-farm activities but are highly constrained in their ability to do so as there are limited non-farm economic opportunities. Likewise at the household level, asset-poor households despite having higher incentive to engage in non-farm activities, will be constrained by their lack of asset and are mostly pushed to low-remunerative activities for lack of choice or due to distress.

The driving forces of demand-pull and distress-push processes are approached by a welfare model, which explains that the labour allocation processes is mainly prompted by wage differences (Möllers & Buchenrieder, 2005). Hence, in situations where the wage rate in the non-farm sector is not higher than the average wage rate in agriculture, diversification into non-farm activities may follow the distress-push path. On the other hand, the demand-pull path can be motivated by a higher wage rate in the non-farm sector. The model also shows that the benefits do not only accrue for demand-pull shifters, who take up better paid non-farm employment, but also for distress-push shifters who, despite engaging in low-paying activities, benefit from increased aggregate household income (Möllers & Buchenrieder, 2005).

The demand-pull and distress-push framework also explains the distinction between diversification for necessity and diversification by choice (Hart, 1994). In other words, diversification may occur either as a deliberate household strategy (Stark, 1991) or as an involuntary response to crisis (Davis, 2003).

Similarly, Ellis (1998, 2000) uses the Sustainable Livelihoods Framework (SLF) to illustrate the context within which rural nonfarm activities are undertaken. In this framework, different livelihood activities pursued by rural households are enabled or constrained by access to capital and assets, in the context of institutions and social relations, and are modified by trends and shocks, with varying effects on livelihood security and environmental sustainability. The SLF can be complemented by the demand-pull/distress-push concept that offers a set of motives, which prompt households to diversify. This paper mainly employs the demand-pull/distress-push approach to investigate the determinants of non-farm participation and returns using a set of variables that reflect incentives and constrains to participate in the rural non-farm economy that pertains to the Ethiopian context. **Table 1** gives a summary of the push and pull factors.

**Table 1: A summary of demand-pull/distress-push factors for non-farm diversification**

| Level | Push factors | Pull factors |
|---|---|---|
| **Micro** | Risk reduction<br>Diminishing returns in land and labor or coping with inefficiency<br>Seasonality<br>Compensating for failures in credit markets/liquidity constraints | Gradual transition to new activities<br>Building on complementarities between activities, e.g. crop-livestock integration.<br>Comparative advantages based on the existence of skills, resources and technologies |
| **Macro** | Incomplete or weak financial systems<br>Constraints in labor and land markets<br>Lack of support to agricultural prices<br>-Population pressure<br>-Climatic uncertainties | Commercial agriculture<br>Location (proximity to urban centers) |

Source: compiled from Barrett et al. (2001) and Deshingkar (2004:3)

## 4. Literature Review

The literature on household income diversification into rural non-farm activities can be divided into two main groups. In the first category, we have several studies that deal with the determinants of non-farm employment and income diversification (Ellis, 2000; Woldenhanna & Oskam, 2001; Barrett et al., 2001; Corral & Reardon, 2001; Escobal, 2001;Yúnez-Naude & Edward Taylor, 2001; Lanjouw, Shariff, and Rahut, 2007; Lemi, 2010). The second group of literature looks into the impact of diversification on household welfare, poverty and inequality (Berdegué, Ramírez, Reardon, & Escobar, 2001; Kijima, Matsumoto, & Yamano, 2006; Minot, 2006; Van Den Berg & Kumbi, 2006; Haggblade, Hazell, & Reardon, 2010; Akaakohol & Aye, 2014). This paper surveys the first group of literature that investigated the determinants of non-farm diversification. **Table 2** below provides a summary of some of these studies.

**Table 2: Summary of some studies on the determinants of non-farm diversification**

| Authors | Country | Data, sample size and methods | Significant determinants |
|---|---|---|---|
| Escobal (2001) | Peru | Living Standard Measurement Studies (LSMS) (1985-97); 2,284 households; Tobit double-censored estimations | education, access to credit, access to roads and electricity |
| Abdulai & CroleRees (2001) | Mali | farm household survey of 1993/94 - 1995/96; 120 households; conditional fixed-effects logit model | education, capital (asset) and location |
| Lanjouw et al.(2007) | India | large rural data (1993-94); 32,000 households; Multinomial logit | Education and land holding |
| Dimova & Sen (2010) | Tanzania | household panel data from the Kagera Health and Development Survey (KHDS) ( 1991-1994), 800 households; fixed and random effects models | household size, dependency ratio, credit, and access to motor road |
| Atamanov and Van Den Berg (2011) | Kyrgyz Republic | two national household budget surveys (2005 & 2006); 1,800 rural households; probit and double-hurdle model | human capital (gender and education), access to infrastructure and cash resources. |
| Sendaza (2012) | Ghana | Ghana Living Standard Surveys (GLSS) (2005/6); 8,700 households; Poisson regression and tobit (double censored) methods | Age, education, access to credit, access to electricity, and markets |
| Akaakohol & Aye (2014) | Nigeria | 120 households; logistic regression | Education, access to credit, farm experience and distance to market (location) |

The literature indicate that the rural non-farm sector is gaining importance in most developing countries, even if agriculture remains the main source of income and employment. In this regard, Haggblade, et al. (2007) note the increasing importance of non-farm diversification in the developing world, especially for households with unstable farm income. Lanjouw et al. (2007) also emphasize the role of the non-farm sector as a potential safety net for households that are mainly engaged in farming.

Empirical studies show that about 30 to 50 % of rural household income in sub-Saharan Africa is typically derived from non-farm income sources (Reardon, 1997, cited in Ellis, 1998; Haggblade et al., 2010). In some regions, for example in Southern Africa, it reaches up to 80 to 90 %. In South Asia, where many landless families wholly depend on non-farm income as source of survival, the average proportion is around 60 % (Ellis, 1998). A figure frequently cited for Ethiopia is 36 % (Degefa, 2005) and a recent study estimates that 25 % of rural households participate in the non-farm sector (World Bank, 2009).[23]

Escobal (2001) using three national surveys from rural Peru from 1985-97, examined the determinants of non-farm income diversification for 2,284 households. The results show that households with sufficient education, access to credit and roads and electricity are able to take on non-farm employment such as handicrafts making, repairing and renting equipment and trade.

Ruben and Van Den Berg (2001) analysed the role of non-farm for 2,727 rural households in Honduras using national income and expenditure survey from 1993 to 1994. They used Logistic regression and find that education, large household size, having more female adults, and location (in Northern regions of Honduras, where industrial free zones have established).

[23] These figures are likely to include off-farm activities as the literature on diversification lacks a standard convention to classifying non-farm and off-farm activities (Barrett et al., 2001).

Using data from a large-scale National Socioeconomic survey, Berdegué, Ramírez, Reardon, & Escobar (2001) studied the evolution of rural non-farm employment in Chile during 1990-96. They applied probit and OLS regression linked by two-stage Heckman model on a large sample consisting of 25,793 and 35,730 households in 1990 and 1996 respectively. They found that the determinants of rural non-farm employment are related human capital variables such as age and gender of household head, schooling, access to credit and physical capital. Moreover, the quality of roads and economic dynamism of the study zones determine the level of non-farm income.

Lanjouw et al. (2007) in their study of non-farm employment in India, used a large rural data from 32,000 households for the year 1993–94 and find that education wealth, caste, village level agricultural conditions, population densities, and other regional effects determine access to non-farm occupations. They used multinomial logit estimates of non-farm employment probabilities and highlight that education increases non-farm employment and income while larger landholdings reduce the chances of participating in non-farm activities.

Pham, Tuan, and Thanh (2010) used the Vietnam Household Living Standard Surveys (VHLSS), 1993–2006 with 9,189 households and analysed the determinants of participation in rural non-farm sector. They used a multinomial logit model and find that individual and community level characteristics such as education and household size have positive effects on non-farm participation. Dependency ratio and landholding negatively affect participation. Further, they report the positive impact of physical and institutional factors, mainly access to public transport on non-farm participation.

Abdul-Hakim and Che-Mat (2011) investigate farm households' participation in off-farm employment using a logit model on primary data from 384 households in the Kedah Darul Aman region in Malaysia. They find that education, gender (male), land size and location in industrial area have positive effects on participation while dependency ratio, age and household size decreases off-farm/non-farm participation.

Atamanov and Van Den Berg (2011) used two national household budget surveys from the Kyrgyz Republic and analysed factors influencing participation and returns from different types of non-farm activities for 1,800 rural households in 2005 and 2006. They applied probit model for primary participation in non-farm activities and double-hurdle model to determine participation and income from non-farm activities. They find that human capital (gender and education), access to infrastructure and cash resources determine both access to non-farm activities and the size of income from the activities.

Using a four-period panel data from Cambodia from the years 2001-2011 and applying fixed and random effects models, Kimsun and Sokcheng (2013) find that the number of male household members aged in the active age group, durable assets, agricultural land endowment, crop failure, are among the prominent determinants of income diversification. Moreover, they find evidence that accumulation is the main motivation for household's diversification into non-farm activities.

Abdulai and CroleRees (2001) study the determinants of income diversification in Southern Mali. Data were pooled from a farm household survey from the 1993/94 and 1995/96 consisting of 120 households and a Conditional fixed-effects logit model was used. The results show that lack of capital and location (being remote from markets) limits diversification while education increases participation in non-farm activities. The study also indicates entry-constraints in diversification and recommends improving infrastructure.

Smith et al. (2001) based on a qualitative and quantitative analyses of data from two districts in Uganda, studied the patterns and determinants of livelihood diversification across the two districts. They find that service provision such as access to formal sources of credit and rehabilitation of road networks are the main determinants of non-farm diversification.

Senadza (2012) examine the pattern and determinants of non-farm income diversification in rural Ghana using data from Ghana Living Standards Survey (GLSS) conducted in 2005/6 on 8,700 households. The number of non-farm income sources is estimated by applying Poisson regression and the results indicate that household characteristics such as age and education, access to credit, electricity and markets are the main determinants of non-farm activities and income.

Babatunde and Qaim (2009) used data from a household survey carried out in 2006 on 220 rural households in Nigeria and study the determinants and impacts of income diversification. They employed the number of income sources as a measure of diversification. The results of their Tobit and Poisson regression show that education, assets, and access to social facilities such as access to water and piped-water, and roads are positively associated with income diversification. Using a two-stage least square technique, they also find that the diversification is pursued as a means of accumulation as the rich households are diversifying more than the resource poor.

Akaakohol and Aye (2014) examine the determinants of diversification in Nigeria using a sample of 120 households. The results of their Logit estimations show that education and access to credit increase diversification, while farming experience and distance to market negatively affects off-farm/non-farm activity participation.

***Diversification in Ethiopia***

In rural Ethiopia farming is the main source of livelihood for the overwhelming majority of farming households, but it has long been established that households tend to diversify their income sources (Demeke & Regassa, 1996; Degefa, 2005). Accordingly, rural households are usually engaged in multiple activities both within agriculture and non-farm sectors. Some households depend exclusively on crop farming for their livelihoods while others on mixed-farming and also try to exploit opportunities of rural non-farm activities in densely populated areas (Dercon & Krishnan, 1996; Demeke, 1997).

Similar to most developing countries, the importance of non-farm activities in the livelihoods of rural people in Ethiopia varies by region (Carswell, 2002). For instance, results from a survey conducted in five regions (Amhara, Tigray, Oromiya, South region and the sedentary farming areas of Afar) shows that while 44 per cent of households were engaged in temporary agricultural work (an off-farm activity) or non-farm activities in previous years, the average contribution of these activities to total household income was only 10.2 per cent (a survey by Ministry of Labour and Social Affairs', 1997 cited in Sharp et al., 2003). However, in Wollo (a North-Eastern province frequently hit by drought) only 26 percent of households had a second occupation such as petty trading, daily labouring, or handicrafts (Sharp et al., 2003). Such low participation to off- and non-farm activities suggest the existence of substantial entry barriers. Woldenhanna and Oskam (2001) in their study of income diversification Tigray in North Ethiopia using a Tobit and multinomial logit on a sample of 402 farm households documented some of these entry barriers. Their result show that households diversify into non-farm activities according to their wealth category. Poorer households mostly engage in off-farm wage labour whereas wealthier households are able to enter higher return activities such as masonry, carpentry and petty trade.

Another study by Block and Webb (2001) based on a survey of 300 households find that wealthier households tend to have more diversified income sources. Also, using median regression they find that age of household head, higher dependency ratio, and farm assets increase chances of income diversification.

Similarly, Demissie and Workneh (2004) in their study of diversification in south Ethiopia, indicate that asset ownership, especially livestock, plays a major role in influencing households' decision to diversify into non-farm activities. Moreover, they show that labour, both in terms of its quantity and quality, determines the choice of diversification as this overcomes entry barriers to non-farm activities. Factors such as land size, cash crop production and agricultural extension services did not encourage households to engage in non-farm diversification activities.

Lemi (2010) investigates the determinants of diversification using the Ethiopian Rural Household Survey (ERHS) of the first and second rounds and finds that age of household head and number of female family members increases participation in non-farm diversification.

A recent study by Demissie and Legesse (2013) apply multinomial logit and tobit models on a cross-sectional survey of 120 households and assess that the participation in non-farm activities and the level of returns depend mainly on human capital ( age and economically active member and education), livelihood assets and infrastructure ( proximity to market).

Dercon and Krishnan (1989) reported by Ellis (2000:35) highlight how in five regions in Ethiopia the share of non-farm income across all regions was low owing to policy constraints on trade and wage labour. However, looking at the wealthier groups, rich households tended to engage more in non-farm activities that require investment and skills (such as carpentry) while the poorest households were likely to engage in less rewarding off-farm activities such as firewood collection. These findings suggest wealthier households are drawn towards non-farm diversification in an attempt to accumulate. A further study by Deressa, Hassan, and Ringler (2008) on farmers' vulnerability to climate change also shows the importance of pull factors: here, a greater degree of access to technology (farm inputs in the form of pesticides, fertilizers, and improved seeds) and proximity to infrastructure were found to be critical for engaging in non-farm diversification.

However, the literature is not in full agreement on this matter. A study by Tegegne (2000) in two districts in the South of Ethiopia found one pull factor (proximity to urban centers) but also two push factors (low crop yields and density of rural population) as the most important variables influencing diversification. More importantly, a recent study by Sosina, Barrett, and Holden (2012) finds that non-farm income positively correlates with household's consumption expenditure growth across *all* wealth groups in Ethiopia. Pulling the studies together, two main positions are advanced in the literature: first, that non-farm diversification is caused by pull/accumulation factors and mainly conducted by wealthier households; and second, that it is caused by both pull/accumulation and push/distress factors.

Push factors such as rural population growth, farm fragmentation and declining agricultural productivity are commonly-cited causes for diversifying into non-farm activities (Degefa, 2005; Sosina & Holden, 2014). Moreover, studies show that pull factors such as urban or local demand, can lead to non-farm activities, enhancing the household's economic standing (Yared, 1999). Thus, rural households tend to engage in a variety of non-farm activities including food-for-work schemes, grain trading, petty trading, migration, liquor sales and the sale of handicrafts (Yared, 1999; Degefa, 2005).

In general, the empirical studies reviewed so far have identified several factors that determine participation and earnings from non-farm activities. These factors can be categorized into individual and household characteristics such age, education, gender, household size, dependency ratio, land holding, assets, and income; and community characteristics such as distance to markets, proximity to towns, and access to physical infrastructure such as roads. However, there is no agreement in the direction and magnitude these determinants, due to mixed results in the empirical literature.

## 5. Data and Empirical Approach

### 5.1. Description of the Data

This part of the paper uses data from the Ethiopian Rural Household Survey (ERHS) for the period 2004–2009.[24] It is a panel household survey that includes 1,306 households in 15 districts of rural Ethiopia. The surveys cover four major regions (Amhara, Tigray, Oromya and South) where the country's largest proportion of settled farmers are found. The ERHS

[24] The data were collected by the Economics Department of Addis Ababa University (AAU), the Centre for the Study of African Economies (CSAE), University of Oxford and the International Food Policy Research Institute (IFPRI).

surveys are of high quality with low attrition rates and have been used in numerous studies.[25] According to Dercon and Hoddinott (2011), the ERHS surveys can be considered as broadly representative of households in non-pastoralist farming systems although not nationally representative. Although the information contained in all survey rounds is fairly consistent, there are modules present in the 2004 and 2009 rounds that are not included in previous surveys. These modules mainly include questions about covariate shocks related to major climatic events such as droughts and flooding, access to electricity and roads and for this reason, this paper uses the two recent surveys.

Between the two recent survey rounds (2004 and 2009), fundamental changes occurred that shaped the microeconomic structure of the rural economy, in particular the high food price inflation ( Uregia et al., 2012; De Brauw, Mueller, & Woldehanna, 2013). These changes are exogenous factors to households' income diversification and thus the time between these survey rounds can be utilized to assess the effects of changes and to determine their impact on non-farm diversification.

In all survey years, households were asked about their participation in a range of activities and the income obtained from these activities in the past four months.[26] Data on income are both in monetary values and in-kind quantities (which have been changed to monetary values). Conversion factors, constructed at Peasant Association (PA) levels and provided by IFPRI along with the official version of ERHS data, were used to convert local units to

[25] Until, 2010 the number of publications that have used the ERHS data in their analysis have reached 303 with 77 journal articles, 4 books and 26 book chapters with more than 3,000 citations (Renkow & Slade, 2013).

[26] This reporting period offsets the problem of memory lapse and can be taken as ideal time to capture income from various activities in the immediate season before the surveys (The surveys were conducted between April and June which largely correspond to the Belg season (short-rainy season) and the four months prior to this period largely refers to the Bega (dry season)–an ideal time for engaging in nonfarm activities).The downside of this is, however, lack of reporting activities that household engaged in the other seasons (e.g. farming season). Thus, it is likely that households may have underreported income earned from some activities.

standard (metric) units. The units include local measurements for area and weight.[27] These units were converted into kilograms by using the conversion factors that are included in the data sets based on surveys on local measurement units that took place during round 3 of the survey (Dercon & Hoddinott, 2011).

For missing units, the median conversion unit at the next aggregate level i.e. district or region was used. Following Bachewe (2009), after converting the in-kind amounts to standard units, nominal prices available at PA level for each round of survey, were used to obtain the monetary value of the items. Items with missing prices have been estimated using the median prices at the next aggregate level. Moreover, for few items that still have missing price information, average retail prices from the Central Statistical Agency (CSA) are used that corresponds to the season and district are used.[28]

Since food represents around 75 % of the consumption basket for the surveyed households, consumption was deflated by a food price index calculated as a Laspeyres index, based on peasant association prices and using average shares in 1994 as weights (see also Dercon et al., 2012). The same food price indices are also used to deflate the value of farm and non-farm income of households. Thus, all incomes are expressed in real terms using 1994 prices.

As explained before, the ERHS data set is ideal for the study of rural non-farm diversification as it has a range of variables that relate to activities and income. Besides, it furnishes detailed

[27] These units differ for each region and district, which requires changing to standard units of measurement. For instance, "chinet" and "dawela"are frequently used in most regions as weight measurements but differ in terms of the PA and type of item in their conversions into metric units. For example, in Shumshea PA, Amhara region, both 'chinet' and 'dawela' are equated to 30 kgs, while the same units are converted into 50 and 100 kgs respectively in Sirbana-Goditi PA of Oromia region.

[28] There were 27 items in 2004 that did not have data on prices at any level in 2004. In 2009, these items were only 12. Beet root, fenugreek, groundnuts, turmeric, field peas, and linseed are among the common items that lacked price data.

information on household characteristics including measures of asset wealth, consumption, production, and shocks from which can be used to draw explanatory variables. The data set however is not without limitations one of which has to do with the exclusion of the pastoralist or agro-pastoralist livelihood zones that represent the most vulnerable livelihood systems in the country. Hence, it cannot be considered representative of the whole of rural Ethiopia.[29]

Moreover, the data set does not contain detailed information on all types of household labour supply. This has limited the possibility of studying the relationship between labour supply decisions and particular non-farm activities, mainly migration. As a result, we are forced to rely on ex-ante information–income from remittances, as a proxy for capturing migration.[30]

This study uses both the number of non-farm activities and income earned from non-farm activities as measures of non-farm diversification. Negative binomial regression is used to estimate the number of non-farm activities while a double-hurdle, fixed and random effect models and instrumental variable regression are employed for the estimation of the determinants of the level of non-farm income. These methods are described in detail in section 5.3 and 5.4. Before we embark on that discussion however, the selection of explanatory variables, their relationship to one another and the expected relationship to the dependent variable are briefly explained in section 5.2 below.

[29] According to Dercon, Hoddinott, and Woldehanna (2012), pastoral areas were excluded from the ERHS because of the problem of tracing and re-surveying such highly mobile households over long periods of time.

[30] Migration is recognized as one of the most important form of diversifying income for rural livelihoods (Ezra and Kiros, 2001). However, there seems to be a lack of consistency in the classification of migration in the literature. Some writers consider migration as a diversification strategy in its own right (Sabates-Wheeler et al., 2008), while others treat it as part of the non-farm sector (Ellis, 1998; Reardon, 1997). For ease of analysis this study leans towards the latter classification and treats migration as part of non-farm activities.

## 5.2. Selection of Variables

Based on the review of the empirical literature, the determinants of non-farm diversification can be summarized into the following categories (see Reardon et al.1998; Barrett et al., 2001; Corral & Reardon, 2001; Escobal, 2001; Janvry & Sadoulet, 2001; Woldenhanna & Oskam, 2001; Lanjouw et al., 2007; Kimsun & Sokcheng, 2013): (1) Human capital variables (household size and composition such as age, gender, education); (2) Location variables (distance to markets and towns, availability of electricity) (3) Initial household wealth ( durable assets) (4) Financial assets (access to credit) (5) Risk indicators (exposure to shocks).

### Hypothesis and expected signs of determinants

The human capital variables mainly household size, age, and education are expected to increase the labour, the experience, the know-how, and the skills important to engage in non-farm activities. Thus, household size and education can be expected to positively influence non-farm income diversification. Larger household size may suggest the availability of more labour, which can participate in non-farm occupations.

Age can have both negative and positive effects on non-farm diversification. This is because as the head or an active member of the household gets older, he or she is likely to be less active. Thus, having more active household members within the economically productive age group (i.e. between 15 and 64) is likely to increase a household’s participation into non-farm income generating activities. In this study, this condition is captured by using dependency ratio at a household level, which is also assumed to qualify household size.

Women-headed households are generally expected to increase their participation in non-farm earning activities given the rigid and patriarchal agricultural division of labour that limits women's employability in farming rural Ethiopia. For instance, Sosina et al. (2012) citing the study by Bevan and Pankhurst (1996), on the 15 villages included in the ERHS data set indicate that ploughing, a major agricultural activity, is only undertaken by men. However, the participation of women in non-farm activities is also limited to less-remunerative activities such as selling food and drink due to their limited asset base.

Agricultural-specific assets mainly land is hypothesized to have both negative and positive coefficients, depending on the main motive behind non-farm diversification i.e. accumulation or survival. Accordingly, having more land may mean higher farm income and lessens the need to take up non-farm employment for those who are motivated to diversifying income as a fall back strategy (risk-minimization). In order to control this effect, crop income is used in the models. If the motive is asset accumulation, then increased land holding may not decrease non-farm diversification. Clearly, one has to control for initial wealth of the household in order to identify the effect of land holding on non-farm diversification. In view of this, initial wealth, which by itself is also an important determinant of non-farm participation (see Reardon et al., 2000; Loening & Mikael Imru, 2009;Sosina & Barrett, 2012), is captured through livestock holding and durable assets (index).

Livestock holding is central in smallholder agriculture systems as source of cash, a substitute for credit market and as a store of value (Ellis & Freeman, 2004; Lemi, 2006). Thus, livestock as an asset can be expected to have a positive relationship with non-farm diversification as it helps to cover the finances required to invest in non-farm activities.

Access to market is expected to have a positive impact on non-farm diversification. It sustains non-farm enterprises through continuous demand for goods or services or helps to create new non-farm activities to meet emerging demands. Distance to nearest town (with a market) from a village is used as a proxy to access to market. Thus, shorter distance to the nearest town (market) is expected to positively impact non-farm diversification as it relatively reduces the transaction and transport costs than would be the case for a distant market. Similarly, access to credit and electricity are also expected to positively affect non-farm diversification.

Apart from these variables, which largely signify household capacities and incentives to participate in non-farm diversification, one has to also take into account the role of risk indicators as determinants of non-farm diversification (see Reardon et al., 1998). Thus, risk indicator variables in the form of exposure to shocks of both idiosyncratic (illness and death of a working household member) and covariate (climatic hazards) are included in the models.

### 5.3. Participation and Returns Models and Econometric Approach

As explained before, for the analysis of the determinants of non-farm diversification, measured by the number of non-farm activities, we have used count data models since the outcome variable is a discrete variable.[31] The standard count data models are Poisson and negative binomial regression and depending on the nature of the count-data other variants of these models can be used. Thus, if there are many observations or individuals with many zero counts, the zero-inflated Poisson (ZIP) or the zero-inflated negative binomial (ZINB) models

[31] Discrete count outcome variables violate basic assumptions of the Ordinary Least Square (OLS) model. OLS assumes that the response variable takes a continuous value, to be normally distributed, and linearly related to the explanatory variables (McClendon, 2002).

are suggested to be more appropriate (see Greene, 2008;Cameron & Trivedi, 2010; Allison, 2012).

### 5.3.1. The Poisson and the Negative Binomial Regression Models

Poisson is one of the count-data models that is widely applied in situations where a dependent variable is discrete (Cameron & Trivedi, 2010). Some studies have also used this model to analyse the determinants of non-farm diversification (see Olivia & Gibson, 2008; Sendaza, 2012).

In the Poisson model, the observed number of non-farm activities for each household, $y_i$ is assumed to be drawn from a Poisson distribution with mean $\mu_i$, where $\mu_i$ is estimated from observed characteristics (Wooldridge, 2008; 2010).

$$\mu_i = E(y_i|\mathbf{X}_\mathrm{i}) = \exp(\mathbf{X}_\mathrm{i}\boldsymbol{\beta}) \tag{1}$$

The exponential $\mathbf{X}_\mathrm{i}\boldsymbol{\beta}$ ensures that $\mu_i$ stays positive, since counts can only be zero or positive.

$$\boldsymbol{P(y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!}} \tag{2}$$

Where: $\boldsymbol{\mu}$ = expected count (and variance) and

$\boldsymbol{y}$= observed count

The Poisson model assumes that the conditional variance of the dependent variable (in our case, number of non-farm activities) is equal to the conditional mean. This is a strong assumption called ‘equidisperson’ (Greene, 2008; Cameron & Trivedi, 2010).

However, in most cases, this assumption cannot be fulfilled as the conditional variance is greater than the conditional mean for most count data sets, which is referred as over-dispersion (Wooldridge, 2010; Allison, 2012). Over-dispersion is most often caused by highly skewed dependent variables. In our case, due to the high numbers of zeros in the number of non-farm activities reported in the data, making the distribution of the outcome variable to be highly skewed (see **Figure 1** annex).

An alternative model, which corrects for such over-dispersion in the data is the Negative binomial model (NBM) (Cameron & Trivedi, 2010). The NBM modify the Poisson model to address over-dispersion by including a disturbance/error term to the Poisson model. The NBM therefore has a less restrictive assumption, which accounts for the fact that the variance may not necessarily be equal to the mean (Greene, 2008).

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$$Var(y|\mathbf{x}) = \boldsymbol{\mu} + \boldsymbol{\alpha}\boldsymbol{\mu}^2 \tag{3}$$

Where: the parameter $\alpha$ represents the extent of over-dispersion

If $\alpha = 0$, the model reduces to simple Poisson regression;

If $\alpha > 0$, over-dispersion; and

If $\alpha < 0$, under-dispersion

Before choosing between Poisson and negative binomial regression, one has to measure the distribution of the dependent variable to check if the Poisson assumptions can be observed (Piza, 2012). This involves running a simple Pearson Chi-Square goodness-of-fit test, which is incorporated with an exploratory Poisson regression model. The test helps to identify the distribution of the data and ensures the selection of the correct statistical model (Cameron &

Trivedi, 2010). Accordingly, the Pearson goodness-of-fit test result for non-farm activities, indicate that the distribution significantly differs from a Poisson distribution, giving a *p*-value of 0.000 (Prob > chi2), which falls far below the standard threshold of 0.05. Therefore, we fit a negative binomial model for the over-dispersed count data (see **Table A,** annexed). In addition to this test, we have run a series of graphical inspections to identify the model that best fits the data. As expected, the distribution of non-farm activities relatively fits well the negative binomial distribution than the Poisson distribution (see **Figure 2** annex).

Another particular feature of our chosen dependent variable is that there are 'excessive' numbers of households with 0 counts. In this context, a special case of negative binomial model, the zero-inflated negative binomial (ZINB) model can be more efficient than the conventional negative binomial (see Greene, 2005; Cameron & Trivedi, 2010;Allison, 2012). The ZINB is a two-part model and assumes that the dependent variable is composed of two types of groups: a group who have a zero probability of a count greater than zero and a group whose counts are generated by the conventional negative binomial regression model (Allison, 2012). In other words, the ZINB model deals with the zeros in two different ways. First, it lets the zeros occur as an outcome of the binary process (0, 1) and second, as a realization of the count process (0, 1, 2, 3…). For example, a household either participates in non-farm activities or not (this is the binary decision process with 0 and 1 options) if the household decides to participate, the number of non-farm activities they can take up is 0, 1, 2, 3, etc. Thus, a household may choose to participate in non-farm activity but not necessarily engage in the activity in a given period of time, which generates the excess zeros in the data.

Despite the theoretical appeal of the ZINB model, in practice the model can only best fit to certain situations where a probability of having a greater than zero count is a rare occurrence, such as for instance, the number of children born to a sample of 60-year-old women (see Allison, 2012). In our case, the zeros in the number of non-farm activities are mostly the results of the data generating process and therefore do not reflect the rarity of non-farm activity participation. In fact, the notion that farm households across the developing world participate and earn an increasing share of their income from non-farm sources has long been established (see Reardon et al., 2007). For this reason, our analysis relies on the conventional negative binomial model.

The regression model for the full negative binomial Model is given as:

$$\mathrm{P}(\mathrm{y} \mid \boldsymbol{X}) = \frac{\boldsymbol{\Gamma}\left(\boldsymbol{y}+\boldsymbol{\alpha}^{-1}\right)}{\boldsymbol{y}!\,\boldsymbol{\Gamma}\left(\boldsymbol{\alpha}^{-1}\right)}\left(\frac{\boldsymbol{\alpha}^{-1}}{\boldsymbol{\alpha}^{-1}+\boldsymbol{\mu}}\right)^{\alpha^{-1}}\left(\frac{\boldsymbol{\mu}}{\boldsymbol{\alpha}^{-1}+\boldsymbol{\mu}}\right)^{y} \tag{4}$$

Where y is the number of non-farm activities undertaken by the household members in the 12 months prior to the surveys.

$\boldsymbol{\alpha}$ as explained under equation 3, represents the extent of over-dispersion**.** If $\boldsymbol{\alpha} = 0$, the model reduces to simple Poisson regression.

**X** includes a vector of variables that are believed to determine a household's participation in non-farm income generating activities. These include individual and household characteristics such as age and gender of household head, education, dependency ratio, household size, agricultural assets (land and livestock), other durable assets, access to electricity, location ( distance to nearest town or major market), access to credit.

### 5.3.2. The Tobit and Double-hurdle Models

This section examines the determinants of non-farm diversification using income as a measure of the level of household's diversification. Our dependent variable in this case is the level of income earned from non-farm activities, which is a continuous variable. In the data set, a significant sample of households (33 %) did not report income from non-farm activities, which resulted in a highly skewed distribution with many zeros. As explained before, the Ordinary least-squares (OLS) regression would give both biased and inconsistent parameter estimates if a dependent variable has many zeros (Cameron & Trivedi, 2010). The conventional approach to deal with such data is to use a class of limited dependent-variable models or censored regression models, namely the standard tobit and double-hurdle models. The following section briefly discusses these models in their analytical forms and provides a rationale for their adoption.

The standard Tobit model originally formulated by James Tobin (1958) is the first model to attempt to handle a censored dependent variable. It attributed the censoring to a standard corner solution (Bierens, 2004; Burke, 2009). The Tobit model assumes that the observed dependent variables $Y_i$ for observations i = 1..., *n* satisfy

$$Y_i = \max\left(Y_i^{*}, 0\right) \tag{5}$$

where the $Y_i^{*}$'s is a latent variable generated by the following classical linear regression model:

$$Y_i^{*} = \mathbf{X}_{\boldsymbol{i}}\boldsymbol{\beta} + \boldsymbol{u}_{\boldsymbol{i}}, \qquad \boldsymbol{u}_{\boldsymbol{i}} \,|\, \mathbf{X}_i \sim \text{Normal}\,(\mathbf{0}, \boldsymbol{\sigma}^{2}) \tag{6}$$

$$Y_i = \begin{cases} Y_i^* & if\ Y_i > 0 \\ 0, & otherwise \end{cases} \quad (7)$$

where the $Y_i^*$'s are latent variable generated by the classical linear regression model with $\boldsymbol{X}$ a vector of regressors, and $\boldsymbol{\beta}$ the corresponding vector of parameters. The model errors $\boldsymbol{u_i}$ are assumed to be homoscedastic and normally distributed (Bierens, 2004).

The condition 7 indicates that we only observe $Y_i^*$ when $Y_i > 0$. Then the zero non-farm income can be interpreted as a left-censored variable (or censored at zero). The censoring can be due to the fact that the surveyed household's did not choose to participate and earn income from non-farm activities (true zero). The observed non-farm income $Y_i$ can also be zero in the following conditions: (1) if there is error in reporting non-farm income in the survey, or (2) if some random circumstance is introduced in the data generating process that may influence a zero response (random zeros)(Carlin & Flood, 1997).

Under a tobit model, the relationship between a vector of predictor variables, $\boldsymbol{X}$, and the latent outcome variable, $Y_i^*$ for a censored observation (at zero) is conditioned by "the same set of tobit coefficients that governs the probability distribution of the censoring outcome and the expected value of the outcome variable given that an individual's outcome score is observed" (Smith & Brame, 2003:368). Thus, the model considers a dependent variable to be censored at zero but ignores the source of zeros (Newman, Henchion, & Matthews, 2003). For instance, non-farm income censored at zero means that the observed zeros can be either "true" zeros (i.e. household's deliberate choice) or censored zeros (i.e. due to data collection process).

Thus, applying this model imposes the assumption that the choice of being censored (participation) and expected value conditional on un-censored (level of participation) are determined by the same parameters (Newman et al., 2003). This assumption tends to be restrictive since it does not take into account the possibility that the zeros may arise for reasons other than non-participation choice, which may not be explained by the same parameters (Martinez-Espineira, 2006).

Moreover, the tobit model cannot handle situations in which the effect of a covariate on the probability of participation and on the size of non-farm income may have different signs (Garcia, 2013). For instance, higher crop income may act as a disincentive to participating in non-farm activities for lack of the need to minimizing agricultural risk. However, the same variable may increase the size of non-farm income by allowing the investment of savings in lucrative non-farm activities for accumulation reason (Atamanov & Van Den Berg, 2011). Clearly, the two effects cannot be determined by the same process.

Heckman (1979) modified the tobit model to include this two-stage estimation procedures with the first step estimating the participation decision i.e. the probability of observed positive outcome and the second step estimating for the level of participation conditional on observed positive values. Accordingly, this model sometimes called Heckit after Heckman (Wooldridge, 2002), allows for the possibility of estimating the first- and second-stage equations using different sets of explanatory variables. However, it assumes that there will be only positive observations in the second stage once the first-stage selection is passed. This assumption may not hold true for some situations such as expenditures in household budgets (see Deaton & Irish, 1984) and tobacco expenditure patterns (see Aristei & Pieroni, 2008). Similarly, in non-farm diversification there are many cases in which households that choose to engage in non-farm activities may not earn income from the activity. This indicates that there is a possibility of observing zero non-farm income in the second-stage decision. Thus, the double-hurdle model (DHM hereafter) that allows for observing zero values in the second hurdle fits with the context of non-farm income than the Heckit model.

The DHM is first proposed by Cragg (1971) was extensively used to analyse a wide range of individual and household commodity demand and labour supply decisions (Deaton & Irish, 1984;Yen & Jones, 1997; Newman, Henchion, & Matthews, 2001; Newman et al., 2003). There are also few studies that have applied the DHM in relation to non-farm diversification. Examples include, a study on off-farm labour allocation decisions among smallholders in Zimbabwe by Matshe and Young (2004) and a study by Atamanov and Van Den Berg (2011) on the determinants of participation and returns from different types of non-farm activities Kyrgyz Republic (central Asia).

In the context of this study, the DHM is used as it provides a general approach to modelling the determinants of participation and returns from non-farm activities as a two-stage decision process. The model is a more flexible alternative than both the tobit and Heckit models and assumes that there are two hurdles to overcome before observing positive values. In our case, the first-hurdle refers to the participation decision and the second hurdle refers to the rate of participation, which is likely to increase the return or extent of income earned from participating in non-farm activities.[32]

Thus, the DHM has a participation (D) equation:

$$D_i = 1 \text{ if } D_i^* > 0 \text{ and } 0 \text{ if } D_i^* \leq 0 \tag{8}$$

[32] Cragg (1971) modifies the tobit model to relax the restrictive assumption inherent in it, namely, that the process that generates variation in the dependent variable, conditional on ability to observe the outcome, is the same as the process that creates variation in the censoring outcome (i.e., whether a household's non-farm income exceeds the censoring threshold (0)) (Smith & Brame, 2003).

The parameters of the participation equation can be estimated independently using a truncated regression model:

$$D_i^* = \alpha \boldsymbol{Z}_i + \boldsymbol{u_i} \;;\;\; \boldsymbol{u_i} \sim \boldsymbol{N}(\boldsymbol{0},\ \boldsymbol{1}) \tag{9}$$

Where $\boldsymbol{D_i^*}$ is a latent participation variable that takes the value 1 if the household participates in non-farm income generating activities and 0 otherwise, $\boldsymbol{Z}$ is a vector of explanatory variables and $\boldsymbol{\alpha}$ a vector of parameters.

The level of non-farm income returns can be given by:

$$Y_i^* = \boldsymbol{X_i \beta} + \boldsymbol{v_i} \;;\;\; \boldsymbol{v_i} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{\sigma^2}) \tag{10}$$

$$Y_i = \begin{cases} Y_i^*, \text{ if } D_i = 1 \; and \; Y_i^* > 0 \\ 0, \text{ if } D_i = 0 \end{cases} \tag{11}$$

Where equation 10 is the same as the tobit equation (6). The difference of the DHM to that of the tobit is expressed by condition 11 that indicates the observed level of non-farm diversification, $Y_i$ is zero either when there is censoring at zero ($Y_i^* \leq 0$) or due to circumstances other than the household's choice pertaining to the data generating process.

The decisions of participating in non-farm income generating activities and the intensity of participation can be modelled (1) jointly, if the two decisions are made simultaneously by the household (2) independently, if the decisions are made separately or (3) sequentially, in which the decision that is made first influences the second decision, which can be modelled by using the dependent double-hurdle model (Martinez-Espineira, 2006; Aristei & Pieroni, 2008). If the decisions are assumed to be made separately, the independence model applies, with independent error terms distributed as follows:

$$\boldsymbol{u_i} \sim N\,(0,\,1)$$

$$\boldsymbol{v}_i \sim N(0, \sigma^2)$$

With the assumption of independent error terms, the heteroscedastic Double-hurdle model can be estimated by the following log-likelihood function:

$$L = \prod_{0} \left[1 - \Phi(\boldsymbol{Z}_i \boldsymbol{\alpha}) \Phi(\boldsymbol{X}_i \boldsymbol{\beta} / \boldsymbol{\sigma}_i)\right] \prod_{+} \left[ \Phi(\boldsymbol{Z}_i \boldsymbol{\alpha}) \frac{1}{\boldsymbol{\sigma}_i} \phi\left((\mathbf{Y}_i - \boldsymbol{X}_i \boldsymbol{\beta}) / \boldsymbol{\sigma}_i\right) \right] \tag{12}$$

This model assumes that the participation and the size/level of non-farm income (returns) are made separately or independently (see Aristei & Pieroni, 2008).

Assuming that there is independence between the two error terms, the log-likelihood function of the double-hurdle model is equivalent to the sum of the log likelihoods of the truncated regression model and the Probit model (Martinez-Espineira, 2006; Aristei & Pieroni, 2008). As demonstrated by McDowell (2003), the log-likelihood function of the DHM can be estimated by maximizing the two components separately. In this study, the log-likelihood function of the DHM was estimated using the user-written programme of Burke (2009) in Stata.

This study uses the independent double-hurdle model with the assumption of independent and normally distributed error terms. However, given the hetroskedastic nature of the data, the assumption of homoscedastic error terms was not achieved and thus a hetroskedastic DHM was applied.[33] The literature on DHM shows that if the assumptions of homoscedastic and normally-distributed errors are violated then maximum likelihood (ML) parameter estimates

[33] The Cragg model in Stata developed by Burke (2009) is used to estimate the DHM by fitting all parameters simultaneously using craggit. This model enables specifying a model for heteroskedastic standard errors in the second-tier estimations without compromising model mis-specification in the first-tier.

become inconsistent (Martinez-Espinera, 2006; Fennema & Sinning, 2007). Some extensions to the double-hurdle model however allow for making corrections for these error specifications. One way to accommodate the assumption of normality is by transforming the dependent and latent variables using box-Cox transformation (Martinez-Espinera, 2006).[34]

The model can be modified to allow for heteroscedasticity by specifying the variance of the errors as a function of a set of continuous variables (Newman et al, 2003 and Aristei and Pieroni, 2008) as follows:

$$\sigma_i = \exp(c_i h) \tag{13}$$

where $c_i$ represents the continuous variables included in $X_i$ variables and *h* represents a vector of coefficients (Yen and Jensen, 1996; Newman et al., 2003; Aristei & Pieroni, 2008).

A likelihood ratio test is also applied to assess whether a normal double hurdle model or a heteroskcedastic version fits the data. The test's assumption is that the homoscedastic double hurdle model ( the restricted model) is nested in the heteroskcedastic double hurdle model (the unrestricted model). The test statistic is computed as follows:

$$LR = -2*(LL_{RM} - LL_{URM}) \sim \chi^2 k \tag{14}$$

where:

$LL_{RM}$ is the log likelihood of the restricted model or the homoscedastic DHM

$LL_{URM}$ is the log likelihood of the unrestricted model or the heteroskcedastic DHM

[34] This transformation was attempted in our analysis. However, the hypothesis test gave much greater support for a log-linear model ($\theta$ = 0) than the linear model ($\theta$ = 1) with the estimate of e = 0.0609. Moreover, the Box-Cox model with is difficult to interpret and use, and in the interest of brevity and interpretation, the log-linear model transformation was preferred in our estimations. See **Figure 3**, annexed for the graphics inspection of normality assumptions.

$\chi^2 k$ is the chi-squared distribution with k degrees of freedom, k referring to the number of variables in the heteroskcedastic equation i.e. the number of coefficients that are assumed to be zero under the restricted model. The Ln of consumption per capita and Ln of annual crop income are included in the heteroskcedastic model and in the homoscedastic model these variables were excluded along with land size and asset index in another model. The results of the likelihood ratio tests are presented in **Table E** (annexed).

**Equation specification and identification**

The choice of explanatory variables for the participation and size of non-farm equations in the double-hurdle model involves some difficulty since the model is not grounded within any formal choice theory (Pudney, 1989). As a result, there is no theoretical guidance regarding equation specifications for the DHM. Despite this apparent shortcomings of the model however, some authors have come up with practical ways to identifying parameters. For instance, Pudney (1989) takes the first-stage or participation hurdle as being primarily affected by non-economic factors than by economic variables such as levels of prices and income. Thus, income and related variables can be excluded from the first hurdle or participation equation. This method has been implemented by many studies that mainly focused on determinants of consumption or expenditure (Yen & Jensen, 1996; Newman et al., 2003, Aristei and Pieroni, 2008). Moreover, Newman et al. (2003) propose imposing exclusion restrictions in DHM since the inclusion of the same regressors in both hurdles can make parameter identification difficult. Cameron & Trivedi (2010) also suggest exclusion restrictions with strong justification for imposing the restriction for more robust identification.

Against this backdrop, the choice of variables for the first and second hurdle equations in this study involved the use of relevant explanatory variables identified from previous studies on non-farm income diversification. Hence, individual and household characteristics such age, education, gender, household size, land holding, durable assets, and community characteristics such as distance to markets, proximity to towns, and access to electricity were used in the first-stage equation. In the second-stage equation, income and risk-related variables that are hypothesized to have impacts on the intensity of participation in non-farm activities were added along with the variables that have significant coefficients in the first equation.[35]

Moreover, adopting the incentives and constrains approach to non-farm diversification, this study reiterate the argument by Reardon et al. (2007) about the how these incentives and constraints create paradoxes at the meso and micro-level (see Section 3). This argument indicates the possibility that the same variable that relate to a community or household's characteristics may increase or decrease participation or returns from non-farm activities through its potentially conflicting effect on incentives and capacity. For instance, livestock holding may decrease the incentive to participate in non-farm activities but it may also ease liquidity constraints and enable farmers to actively engage in activities such as trading or service provision like transportation, which in turn increase their non-farm income.

**Model specification tests**

To identify the model that best identifies the determinants of non-farm income diversification, a series of model specification tests namely, likelihood ratio (LR) tests are

[35] The method of excluding insignificant variables from the second-stage equations has also been used in other studies that applied the DHM (see Jones, 1992;Yen and Jensen, 1996).

undertaken. These tests can be used decide between the tobit and the independent double-hurdle model since the standard tobit model is a nested version of the DHM or Cragg model (Martinez-Espineira, 2006; Aristei & Pieroni, 2008). We first estimate the Tobit model, the Probit model, and the truncated regression model separately (see **Table B**, annexed), and used a likelihood ratio (LR) test. Following Greene (2000), the LR−statistic for this test can be computed as:

$$T = -2 * \left(\log L_T - \left(\log L_p + \log L_{TR}\right)\right) \sim \chi_k^2 \tag{15}$$

where

$L_T$ is the log likelihood for the Tobit model;

$L_P$ is the log likelihood for the Probit model;

$L_{TR}$ is the likelihood for the truncated regression model; and *k* is the number of independent variables in the equations.

We also used a simple test to compare the Heckman selection model against the Tobit model using the following equation:

$$T = -2\left(\log L_T - \log L_H\right) \tag{16}$$

Where $L_T$ is the log likelihood for the Tobit model; and

$L_H$ is the log likelihood for the Heckman selection model

By comparing each pair of log likelihood values in equation (8), we tested the tobit model against the double-hurdle model. The log likelihood of double-hurdle model is given by the sum of the log likelihoods of the truncated regression model and probit model. The results of the specification tests show that the double-hurdle model provides a better fit than the tobit model. Results of the specification tests are given in **Table C** (see annex).

## 6. Results and Discussion

### 6.1. Determinants of Non-farm Activity Participation

In this section, the results of the determinants of non-farm activities participation are presented. The number of income sources (mean distribution) among different types of households is shown in **Table 3**.The maximum number of non-farm activities that households engaged is eight. The number of activities has shown a marked increase between the two survey periods.

**Table 3: Mean distribution of the number of non-farm activities**

| Household categories | Year | |
|---|---|---|
| | 2004 | 2009 |
| Female-headed | 19.75 | 57.80 |
| Male-headed | 25.00 | 62.90 |
| *Wealth category* | | |
| first quintile | 22.00 | 44.84 |
| Second quintile | 23.53 | 64.75 |
| Third quintile | 17.30 | 71.00 |
| Fourth quintile | 23.56 | 69.23 |
| Fifth quintile | 31.00 | 41.34 |
| All | 23.74 | 61.00 |
| Nonfarm activities > 0 | 1.14 | 1.68 |

Source: computed from ERHS 2004–2009.

**Table 4: Determinants of non-farm activity diversification in rural Ethiopia**

| Dependent variable: Number of non-farm activities | (1) NBM | (2) NBM |
|---|---|---|
| Age of household head | -0.0131*** | -0.0119** |
| | (0.00374) | (0.00373) |
| Male head(=1) | -0.0401 | 0.0481 |
| | (0.115) | (0.115) |
| Education of household head | -0.00623 | 0.0103 |
| | (0.0158) | (0.0156) |
| Household size | 0.0825*** | |
| | (0.0195) | |
| Dependency ratio | | -0.585*** |
| | | (0.173) |
| Livestock holding (in TLU) | 0.00347 | 0.00916 |
| | (0.0128) | (0.0117) |
| Credit dummy (=1) | 0.316** | 0.327** |
| | (0.102) | (0.102) |
| Land size ( in ha) | -0.287** | -0.280** |
| | (0.0921) | (0.0904) |
| Ln crop income | -0.0409 | -0.0346 |
| | (0.0302) | (0.0297) |
| Climate shocks index | 0.0656 | 0.0940 |
| | (0.109) | (0.108) |
| Death of a working member | -0.288** | -0.345** |
| | (0.108) | (0.107) |
| Illness dummy | 0.107 | 0.128 |
| | (0.0985) | (0.0968) |
| Access to electricity | 0.317*** | 0.307*** |
| | (0.0934) | (0.0922) |
| Distance to nearest town ( in kms) | -0.0269* | -0.0230* |
| | (0.0107) | (0.0109) |
| _cons | -0.338 | 0.163 |
| | (0.309) | (0.310) |
| No. observations | 1981 | 1981 |
| No. groups | 1142 | 1142 |
| Wald chi2 | 146.7 | 125.9 |
| Prob > chi2 | 0.0000 | 0.0000 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:*

NBM= Negative Binomial Model.
GEE population-averaged model

**Table 4** provides the results of the negative binomial regression models. Most of the determinants of non-farm activity participation relate to household and demographic characteristics. Household size, access to credit, and access to electricity increase the number of non-farm activities in which household participate, while and age of household head, dependency ratio, land size, death of a working member, and distance to the nearest town (market) significantly reduce participation in all model specifications. These results are indicative of the role of household characteristics in non-farm participation decisions. Most of these results are to be expected, except that of education, which has not been found to be a factor in determining activity participation in our estimations. This result is contrary to the positive and significant role of education reported elsewhere in the literature (Barrett et al., 2001b; Abdulai & CroleRees, 2001; Lanjouw et al., 2007). However, most studies that have found education to be significant have used non-farm income as their response variable while we used only the number of non-farm activities participation in our model. Besides, the evidence on education as having a positive implication for non-farm diversification is by no means cut- and-dry as a number of recent studies came up with mixed results. Thus, our result on education corroborates with some previous findings on non-farm diversification that find insignificant results for Ethiopia (see Block & Webb, 2001), for Ghana (Canagarajah, Newman, & Bhattamishra, 2001), and for Malaysia (Abdul-Hakim & Che-Mat, 2011). A possible explanation for the result on education could relate to the nature of non-farm activity participation in the sample districts: it is highly likely that most of the activities that households participate may not require education as in the case of self-employment activities in the informal sector.

The other key demographic indicator that determines non-farm activity diversification is age of the household head. Here, we find that for each additional year of the household head, the number of non-farm activities is likely to decline by 1.17%. This result is consistent with other studies in Africa (see Canagarajah et al., 2001 for Ghana and Uganda) and Senadza, (2012) for Ghana. This result makes sense if viewed from the human capital literature's angle, which generally argues that participation in the labour force declines as one gets older. This result however, only works for number of activities and as we will see from the tobit and double-hurdle estimations for non-farm earnings, age has a slightly positive coefficient. This could mean that once households decide to diversify into non-farm activities, households with relatively older heads are likely to earn more than the younger ones, due to perhaps more experience, accumulated wealth and social capital. Block and Webb (2001) based on data from 300 rural households in Ethiopia reached similar conclusions with respect to household's age and non-farm income. Lanjouw et al. (2007) also find that non-farm income increases with age in rural India.

Household size increases participation in non-farm activities with the number of non-farm activities increasing by approximately 8.6% with every one person increase in the household. Most studies on non-farm diversification agree on the positive effect of household size since it mostly relates to the supply of labour to the non-farm sector (Reardon, 1997; Clay et al.,1995 as cited in Reardon, 1997; Barrett et al., 2001b; Abdulai CroleRees, 2001; Lanjouw et al., 2007). However, one can argue that household size could be a liability for the overall welfare of the household if the number of labour-contributing members is less than the dependents. Thus, in order to capture this aspect of household labour supply, we have included dependency ratio in a second model. The results show that dependency ratio is a key demographic variable that negatively relates to non-farm activity participation. Accordingly, a one unit increase in the dependency ratio is likely to reduce the number of non-farm activity participation of a household by up to 58 %, statistically significant at less than 1 % level. This result on dependency ratio mirrors findings from other studies (see Lemi, 2006; Saha & Bahal, 2010 cited in Kuwornu, Bashiru, & Dumayiri, 2014; Khatun & Roy, 2012).

Participation in non-farm activities seems to be negatively related to the performance of the farming sector. This is partly reflected by the negative and significant coefficient of land size. Thus, if farm size keeps on increasing, farmers may opt to engage in farming activities rather than increasing their non-farm activity participation. The influence of landholdings on participation in and earnings from rural non-farm activities is found to be mixed in the literature. That is to say, landholding may encourage participation in the RNFE serving as collateral to raise capital or increase access to own-capital by raising farm income. On the other hand, by raising farm income, it may discourage participation into the RNFE (Reardon et al., 2007).

Access to electricity is found to be an important and highly significant determinant of non-farm activity diversification. Compared to those households who do not have access to electricity, households that have access are likely to increase the number of non-farm activities by up to 32 %. This result is consistent with what other studies have found elsewhere such as in Peru (Escobal, 2001) and India (Lanjouw et al., 2007).

### 6.2. Determinants of Non-farm Income Participation and Earnings

This section, presents the results of the determinants of non-farm income along with participation model from the standard tobit and double-hurdle models. Annual non-farm income (log-transformed) is used as an indicator of the level of non-farm diversification of households.

**Table 5: Maximum Likelihood Estimation of Double-Hurdle Model for the Ln log of non-farm income**

| | First Hurdle | Second Hurdle |
|---|---|---|
| Age of household head | 0.00635** | 0.00532* |
| | (0.00231) | (0.00254) |
| Male head (=1) | -0.309*** | -0.171* |
| | (0.0726) | (0.0815) |
| Education of Household head | 0.0399*** | 0.0332* |
| | (0.0120) | (0.0150) |
| Household size | -0.0293* | 0.0916*** |
| | (0.0136) | (0.0173) |
| Livestock holding (in TLU) | -0.0259** | 0.00381 |
| | (0.00909) | (0.0113) |
| Credit dummy (=1) | 0.0651 | |
| | (0.0647) | |
| Land size ( in ha) | -0.101** | -0.0105 |
| | (0.0337) | (0.0404) |
| Asset index | -0.0601 | |
| | (0.261) | |
| Climate shocks index | 0.101 | -0.261** |
| | (0.0696) | (0.0807) |
| Access to electricity (=1) | 0.424*** | 0.0360 |
| | (0.0673) | (0.0746) |
| Distance to nearest town | -0.00761 | |
| | (0.00909) | |
| Ln annual crop income | | -0.0519** |
| | | (0.0188) |
| Ln consumption/capita | | 0.224*** |
| | | (0.0498) |
| _cons | 0.724*** | 4.544*** |
| | (0.186) | (0.264) |
| sigma | | |
| _cons | | 1.274*** |
| Log likelihood | -3367.4 | |
| chi2 | 216.8 | |
| Observations | 1977 | 1977 |

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:*
Regional dummies are estimated but not reported.

Source: computed from ERHS, 2004–2009

**Table 5** presents the results of the double-hurdle model. The coefficients in the first hurdle indicate how a given variable affects the likelihood (probability) to participate in non-farm income generating activity. The second hurdle presents the variables that influence the level/intensity of non-farm income diversification, given that a decision is made to participate in non-farm activities.

The results show that there are some visible differences in the parameter estimates of the variables in the participation and level of non-farm equations. Moreover, except for age, gender, and education all variables do not have similar statistical significance and magnitude in both equations. Accordingly, age of the household head and education significantly increase both the participation and the level of non-farm income. The effect of age in terms of magnitude is very small as each additional year increases the probability of non-farm diversification by only 0.63 % and the level of non-farm income by 0.53 %. Education on the other hand, has a relatively greater effect as each year of schooling results in 3.9 % and 3.3 % increase in participation and returns respectively.

The results on age as a factor for non-farm diversification may indicate that those households with more experienced heads are likely to participate more in non-farm income but with declining rate of returns. The positive result on education is to be expected and consistent with the theoretical literature (Barrett et al., 2001b) and previous findings from Latin America (Taylor & Yunez-Naude, 2000;Yunez-Naude & Taylor, 2001; Escobal, 2001) and from Africa (Abdulai & CroleRees, 2001; Canagarajah et al., 2001; Babatunde & Qaim, 2009). Studies in Ethiopia do not provide a clear indication with regards to the effect of education on non-farm diversification ( see Block & Webb, 2001; Woldenhanna & Oskam,

2001) and some even report negative impact of education particularly on non/off-farm wage employment (Demissie & Legesse, 2013).

The demographic variable of household size has a negative effect on participation while positively affecting the rate/level of return from non-farm income once households engage in such activities. Crop income reduces the intensity or rate of non-farm returns while growth in consumption/capita increases the level of return from non-farm income. These results jointly may hint to the existence of 'push' factors since households who have a viable income from farm activities, may not opt to engage in non-farm activities. Reardon et al. (2000) explain the relationship between farm and non-farm income in terms of seasonal, transitory, and permanent changes relating to farm income. In the first case, farm income may drop below what is needed to survive during off-seasons. Thus, farmers choose to engage in nonfarm activities to smooth income and consumption (inter-seasonal smoothing). Second, a drop in farm income due to some unexpected shocks like drought can result in an ex-post coping through nonfarm activities. The third situation is when there is permanent (inter-year) drop in farm income due to (macro) and meso factors including land redistribution, or reduction in landholding.

Access to electricity has a positive and significant effect on participation. However, once households decide to participate in non-farm activities, their level/rate of return or earnings from their participation seems to be less affected by their access to electricity (see **Table 5**). This is perhaps due to the nature of the non-farm activities that smallholders engage, which are most likely to be less electricity-dependent enterprises because of the requirements of higher capital cost to have one's own electric supply (e.g. diesel-powered grain mills) (see Gordon & Craig, 2001).

Locational characteristics– distance from the nearest town and therefore from a major market, has not been found to have any significant effect both on participation and level/rate of non-farm earning. This is contrary to what has been reported elsewhere in the literature (Escobal, 2000; Canagarajah et al., 2001; Senadza, 2012).

Climatic shocks index (aggregated from self-reported experiences of drought, flooding and frost hazards by households) was included in the model to control for risk and vulnerability factors. The results show that climatic shocks may not be significant in determining the participation decisions but play a role in significantly reducing the rate/level of non-farm income.

Interestingly, consumption per capita has a positive and significant association to the level of non-farm diversification (a 100 % increase in consumption, increases the level of non-farm income by up to 22.4 %, significant at less than 1 %). This is an important finding because of its implication for ascertaining the motivation for engaging in the rural non-farm economy. Thus, this finding requires further investigation as to the extent to which growth in consumption influences non-farm income as well as the direction of causality (which will be discussed in the next section).

In sum, the double-hurdle model help to identify the major factors that influence non-farm income diversification and, compared to the standard tobit model, provides a better estimate by separating factors that affect participation from those that determine the level of non-farm income. In the next section, we will present results from fixed, random effects estimations and Instrumental variable regression in order to cross-check the results from the Poisson, and double-hurdle estimations and establish the direction of causality between consumption and non-farm income. This would also help to understand the motivations behind diversifying decisions.

### 6.3. Determinants of non-farm Diversification-Results from Fixed Effects

As a robustness check, we used data from the four rounds of the ERHS from the years (1994, 1997, 2004 and 2009), with 1240 households per year. The four rounds of the surveys cover an extensive period between 1994 and 2009 and this allows for a robust estimation of the effects of variables that are constant over these time intervals (time-invariant factors) as well as those fixed between households.

#### 6.3.1. Application of Models and Results

As discussed in previous sections, the major determinants of income diversification relate to demography, assets, and income as well as risk indicators in rural settings (Reardon et al., 1998; Ellis, 2000; Barrett et al., 2001; Lemi 2006). Identifying these determinants and knowing whether nonfarm diversification is pursued for accumulation (choice) or survival (necessity) has significant policy implications. If diversification is a survival strategy, "the expected relationship between household income diversification and the household's income will be negative – poor households are likely to diversify more than richer households" (Dimova and Sen 2010:2). If, on the other hand, diversification is a matter of choice, richer households tend to diversify and engage in activities that require more capital such as cottage manufacturing, transport and trade with high returns on labour. The poor will not be able to pursue these activities due to high entry costs and capital requirements (Ellis 2000; Dimova and Sen 2010).

Dimova and Sen (2010:3) in their study of income diversification in rural Tanzania, note that "attitude towards risk may explain household income diversification independent of 'push' or 'pull' factors". The argument here is that if one uses cross-sectional data, the observed relationship between diversification and these factors could be the result of this omitted variable – attitude towards risk. Since the focus of this paper is the determinants of non-farm income diversification, fixed and random effect models will be used. These models help to identify the determinants of non-farm income diversification by separating unobservable household characteristics that may impact on diversification.

The use of Fixed Effects (FE) and Random Effect (RE) models makes it possible to minimize omitted variable biases (Cameron & Trivedi, 2010) and help to control for unobserved household's attitudes to risks (Dimova & Sen, 2010). FE explores the relationship between predictor and outcome variables within an entity (households). Each household has its own individual characteristics that influence the predictor variables. The basic intuition behind the fixed-effects approach is that each individual household will have a different intercept, but the relationship driving the differences of variables from their means is constant across households (Wooldridge, 2010).

If differences across households are believed to have some influence on the dependent variable, in our case, non-farm income, the RE is a more appropriate model. The RE model assumes that the entity's error term is not correlated with the predictors which allows for time-invariant variables such as gender and location to play a role as explanatory variables (Cameron & Trivedi, 2005; Angrist & Pischke, 2008). The RE model also comes with the advantage being able to draw inferences beyond the sample used in the model (Baltagi, 2008;Wooldridge, 2010).

The equation for the Fixed-Effects model is given as follows:

$$y_{it} = \beta_1 \boldsymbol{X}_{it} + \alpha_i + u_{it} \tag{18}$$

Where

$\alpha$ ($i$=1….n) is the unknown intercept for each household ($n$ entity-specific intercepts).

$Y_{it}$ is the dependent variable (ln log of non-farm income) where $i$ = a household and $t$ = time.

$X_{it}$ represents one independent variable (IV),

$\beta_1$ is the coefficient for that IV,

$u_{it}$ is the error term

The Random effects model is:

$$y_{it} = \beta \boldsymbol{X}_{\mathrm{it}} + \alpha + u_{it} + v_{it} \tag{19}$$

where $u_{it}$ is a between-entity error and $v_{it}$ a within-entity errors.

Random effects allow for time-invariant variables to be part of the explanatory variables. As it assumes that the entity's error term is not correlated with the predictors. It also assumes that error variances are randomly distributed across group and/or time.

Since our data do not contain variables that pertain to location and risk indicators for all rounds of the survey, we were not able to include these variables in our estimations. Thus, it was not possible to account for important determinants of non-farm diversification in the fixed and random effects estimations. This is likely to have an implication in terms of limiting the results obtained from the fixed effects model, which need to be interpreted with caution.

**Table 6** shows that the share of income from non-farm activities is varying between 14 to 26.7 percent. This agrees with the findings of Rijkers, Söderbom, and Teal (2008) who estimated the contribution of non-farm income at more than a quarter of total household income in rural areas of Ethiopia. Other studies also report figures which roughly correspond to those of the earlier rounds of the ERHS. For instance, survey findings from five regions (Amhara, Tigray, Oromiya, South region and the sedentary farming areas of Afar ) by the Ministry of Labour and Social Affairs show that while 43.9 percent of households were engaged in non-farm activities in 1996, the average contribution to total household income was only 10.2 percent (Sharp et al., 2003:163). As expected in an agrarian economy, the share of income derived from farm activities by far exceeds other income sources reaching a peak in 1997 (82.64%).

**Table 6: Share of income from different sources 1994-2009**

| Income category | Year | | | |
|---|---|---|---|---|
| | **1994** | **1997** | **2004** | **2009** |
| Share of non-farm income (%) | 16.21 | 14.04 | 17.54 | 26.71 |
| Share of farm income (%) | 71.27 | 82.64 | 77.55 | 70.07 |
| Share of off-farm income (%) | 5.70 | 2.61 | 2.77 | 1.58 |
| Public transfers ( food or cash)* | 6.53 | 0.55 | 1.45 | 1.04 |
| Other sources | 0.28 | 0.16 | 0.68 | 0.59 |

Source: computed from ERHS 1994–2009.

*Notes:*

*public transfers refer to in-kind income that is converted into monetary value. It mainly involves food aid given to destitute farmers that are affected by drought in food insecure districts. Prior to 2005, the transfer was largely emergency food aid. In order to avoid potential source of endogeneity, this income source is treated separately because it is a targeted transfer that reaches to the poorest households.

The results of the fixed and random-effects models are presented in **Table 7**. The Hausman test strongly rejects the hypothesis that the random-effects provide a consistent estimate and thus we base the interpretations of the results on the outcome of the fixed effects model.

**Table 7: Determinants of the non-farm income diversification (Fixed and Random effects), 1994–2009**

| Dependent variable: Ln of annual non-farm income | 1<br>Fixed Effects | 2<br>Random Effects |
|---|---|---|
| Age of household head | -0.00297 | -0.00569** |
| | (0.00505) | (0.00211) |
| Gender of household head(male=1) | -0.0935 | 0.0719 |
| | (0.183) | (0.0673) |
| Highest grade completed | -0.000842 | 0.0582*** |
| | (0.0227) | (0.0103) |
| Household size | 0.0449 | 0.0375** |
| | (0.0332) | (0.0128) |
| Ln consumption/capita | 0.187* | 0.341*** |
| | (0.0919) | (0.0440) |
| Asset index | 0.0130 | -0.0643 |
| | (0.140) | (0.0712) |
| Livestock holding ( tlu) | 0.0685* | 0.0248* |
| | (0.0267) | (0.00999) |
| Landholding size ( in ha) | -0.0333 | -0.117*** |
| | (0.0685) | (0.0300) |
| Access to credit dummy(=1) | 0.00380 | -0.0591 |
| | (0.128) | (0.0634) |
| Access to electricity(=1) | 0.191 | 0.0616 |
| | (0.196) | (0.0780) |
| 1997.year | -0.741*** | -0.558*** |
| | (0.161) | (0.0998) |
| 2004.year | 0.217 | 0.155 |
| | (0.135) | (0.0797) |
| 2009.year | -0.254 | -0.264** |
| | (0.199) | (0.0974) |
| _cons | 4.769*** | 4.447*** |
| | (0.510) | (0.221) |
| *No. obs.* | 2066 | 2066 |
| *No.groups* | 999 | 999 |
| F(13,998) | 4.58 | chi2(16)= 280.67 |
| Prob > F | 0.000 | 0.000 |
| $R^2$( overall) | 0.073 | 0.132 |

Robust and clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*:
The fixed effects are both individual (household) level and time fixed.
The dependent variable is total real annual income from non-farm activities (transformed into the natural log) and values are in real Ethiopian currency (birr) in 1994 prices. The exchange rate was about $1=5.42 Birr in 1994.
Regional dummy coefficients were estimated for the random effects but not reported.
We tested for multi-collinearity using the Variance Inflation Factor (VIF). All variables have acceptable VIF levels of less than 5 and the mean VIF is 1.76.

Hausman Test: Ho: difference in coefficients not systematic
chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 46.66
Prob>chi2 = 0.0000
Where b=Fixed effects, B= Random effects

As reported in **Table 7**, column 1, in the fixed effects estimation most variables do not have significant coefficients and only factors which affect non-farm income are consumption per capita and the size of livestock holding. These results confirm the findings from our previous estimations that used the double-hurdle model and prove the importance of disposable income and flexible capital/asset (livestock) as the major determinants of non-farm diversification. We discuss these findings below.

The coefficient of logged consumption per capita (elasticity of non-farm income to consumption) indicates that a 10 percent increase in consumption/capita is likely to increase non-farm income by up to 1.8 % (significant at the 5 % level).[36] These findings on income partly support the argument that non-farm diversification might be driven by accumulation motives. Similar findings are also reported elsewhere in rural Tanzania (Dimova and Sen, 2010) and in Tigray region in Ethiopia (Woldehanna and Oskam, 2001), in Western Kenya (Olale & Henson, 2012) and in Nigeria (Idowu, Ojiako, & Ambali, 2013).

A further important indicator of household asset (store of wealth) in rural Ethiopia is livestock holding (Mogues, 2004), which in our analysis, positively impacts on non-farm diversification. Additional livestock (given in Tropical Livestock Unit) increases non-farm income by up to 6.8 %. This result on livestock holding, coupled with the positive impact of consumption suggests that asset-rich households are more likely to engage in non-farm activities.

[36] Following (Wooldridge, 2008), we used the following formula in interpreting the coefficients' of the natural log of continuous variables and the untransformed continuous variables respectively.
$\beta = \partial \ln(Y_{1i}) / \partial \ln(X_{2i}) =$ a 100 per cent change in $X_{2,}$ generates a 100* $\beta$ % change in *Y; where* $\beta$ *is the elasticity of Y with respect to X.*
$\beta = \partial \ln(Y_{1i}) / \partial X_{2i} =$ a one unit change in $X_2$, generates a 100* $\beta$ % change in *Y*

### 6.4. Non-farm income diversification, a means of survival or a means of accumulation?

So far this paper has presented evidence that non-farm diversification is determined by a set of pull factors such as education, availability of labour in terms of large household size, growth in income and asset holdings. The positive association between these factors and non-farm diversification may hint to the dominance of accumulation motive in non-farm diversification. Despite this positive relationship however, establishing the direction of causality in this relationship remains a major caveat. Therefore, this section focuses on establishing the direction of causality using Instrumental Variable (IV) approach.

According to Cameron & Trivedi (2010), the individual fixed-effects model of the form:

$$y_{it} = \boldsymbol{X}_{it}\boldsymbol{\beta} + \alpha_i + u_{it} \tag{20}$$

gives consistent estimates of the coefficients of the time-varying parameters under a limited form of endogeneity of the regressors $X_{it}$. These regressors may be correlated with the fixed-effects $\alpha_i$, but not with $u_{it}$. Thus, the Instrumental Variable (IV) regression provides an improved way of allowing for $X_{it}$ to be correlated with $u_{it}$, under the assumption that there exists variables or instruments $Z_{it}$ that are correlated with $X_{it}$ and but not with with $u_{it}$.

The main argument for establishing the direction of causality in this analysis is that non-farm income and consumption/asset holding may jointly depend on individual ability or industriousness (which is not directly observable) or on access to critical infrastructure or services.[37] This may introduce a potential endogeneity that biases our estimations. Some studies have tackled this problem using the IV regression. For instance Dimova and Sen (2010) using data from Tanzania addressed potential reverse causality by using instrumental variables (IVs), such as village level shocks, rainfall variability, education of the head of household and an indicator of whether a working member of the household died during the preceding year.

We adopt a similar procedure used by Dimova and Sen. However, since our data are limited in terms of exogenous variables; we used land quality index, the existence of perennial crops (a village dummy variable) and death of able-bodied member as IVs in our model. These are exogenous variables that are correlated with consumption/income but have no correlation with the error term (unobserved effects). The variables are assumed to impact non-farm diversification through their indirect effect on income, satisfying the exclusion criteria of being an IV.[38]

The results of the IV estimations are presented in **Table 8** where the random effects model show that the coefficient of the endogenous variable representing consumption shows a positive sign in which a one percent increase in consumption per capita would yield almost a closer percent (0.93%) increase in the non-farm income for a household, statistically significant at 5% level. This result give support to the argument that non-farm diversification is mainly pursued as an accumulation rather than a survival strategy in our sample. Our results are similar to those offered by Block and Webb (2001) who also find that greater

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[37] These are important pull factors for non-farm diversification which are lacking in our analysis due to data limitation. These factors however, are to some extent, captured in our model as we have used regional dummies.

[38] The instruments used in the estimations have passed the Sargan–Hansen test of over identifying restrictions. The Hausman test also indicates that the Random effects estimations are consistent than the Fixed effects estimations.

income diversification (out of cropping) was positively associated with high per capita income level.

Such findings may hint that accumulation driven non-farm activities have less impact on reducing poverty in the short-run since the activities are mostly pursued by the non-poor. However, in the long-run, the potential contributions of the non-farm sector to poverty reduction through its effects on creating employment and promoting local growth (see Lanjouw and Lanjouw 2001; Davis and Bezemer 2004; Haggblade et al. 2010) can be realized if the right policy instruments are put in place. These include expanding access to infrastructure and communication services to rural areas to promote the benefits of the rural non-farm economy to trickle-down to the poor mainly through alternative employment and income opportunities.

**Table 8: Impact of consumption on non-farm income, 1994-2009**

| Dependent variable: Ln non-farm income | (RE+IV) |
|---|---|
| Ln consumption/capita | 0.928* |
| | (0.388) |
| Age of household head | -0.00562* |
| | (0.00234) |
| Male household head (=1) | 0.0166 |
| | (0.0811) |
| Highest grade completed | 0.0442** |
| | (0.0170) |
| Household size | 0.0814** |
| | (0.0302) |
| Illness dummy (=1) | -0.0543 |
| | (0.0655) |
| Asset index | -0.0662 |
| | (0.0965) |
| Livestock holding (tlu) | -0.000464 |
| | (0.0173) |
| Landholding (in ha) | -0.104*** |
| | (0.0292) |
| _cons | 2.185 |
| | (1.475) |
| No.observations | 1868 |
| No. groups | 978 |
| $R^2$ | 0.10 |
| chi2 | 217.1 |
| Prob > chi2 | 0.000 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:*
Test: Ho: difference in coefficients not systematic

chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 1.24
Prob>chi2 = 1.0000

Test of over identifying restrictions:
Cross-section time-series model: xtivreg g2sls
Sargan-Hansen statistic 0.103 Chi-sq(1) P-value = 0.7488

The Sargan-Hansen test of over identification tells that the estimation is consistent and that the instruments are valid: p-value is > 5% therefore we accept the Ho- that the instruments are valid.

Land quality and perennial crop dummy are used as instruments in the log of consumption per capita estimation. Regional dummies and year coefficients were estimated but not reported.

## 7. Summary and Conclusions

This paper examined the determinants of non-farm diversification using both activity and income indicators for a panel of rural households in Ethiopia for the period 1994–2009. The analysis indicates that although smallholders are trying to diversify their income sources, the contribution of non-farm income to total household income is very low. This partly reflects the extreme poverty prevalent in the smallholder agricultural system in the country.

The results from our estimation indicate that eight variables– age of household head, household size, education, consumption per capita, asset holding, livestock holding, access to electricity and access to credit, positively affect non-farm diversification. Of these variables, household size is found to have a consistent effect across all model estimations followed by education and consumption variables.

Most of these variables belong to pull factors and indicate inter-household differences in capacities and incentives such as comparative advantages based on the existence of human capital (household size and education) and financial capital (higher consumption, asset and livestock holding) at micro level. At macro level, only one pull factor–access to electricity is found to be significant with its influence limited to determining household's participation or entry into non-farm activities but having no significant effect on the rate of returns from non-farm activities. With regards to proximity to urban centres, we have found no evidence of its role in non-farm diversification in our estimations.

The finding on the role of electricity is consistent with previous studies on the dual role of rural electrification on the non-farm economy (Lanjouw et al., 2007). In general, the role of infrastructure is not as straightforward as it seems. In this regard, Renkow (2007: 197-198) asserts that infrastructure's role varies according to context and type of rural non-farm economy. According to him, infrastructure can be considered as "a double-edged sword": on one side it promotes the development of rural industries serving as a fixed input into the production process. On the other side, infrastructural development may lead to the "crowding out" of remote rural firms by exposing them to higher market competition.

Other variables, such as dependency ratio, landholding, and climatic shocks negatively affect non-farm diversification and have consistent coefficients across many of the model specifications. Taken jointly, these results may indicate the existence of competition over the major factors of production between farm and non-farm activities, particularly labour. This in turn may reflect the lack of labour substituting technologies and the subsistence nature of farming. This condition has long been recognized as an impediment for achieving growth in the non-farm sector. The following quote from FAO's report aptly describes this situation:

> "…[R]igidities in the technology of a given sector may block labour availability for development of the other. For example, a traditional labour-using technology can keep smallholder labour "bottled up" on the farm and thus make it unavailable for off-farm activity. ...Thus, investment in technological change in the farm sector, which may only be accessible to the asset-rich households, is needed to free up labour for the non-farm sector" (Reardon et al., 1998: 322).

In general, the factors that affect non-farm diversification negatively, may also suggest that as long as smallholders have enough factors of production such as land, labour and capital (in the form of assets like livestock and oxen) and farm income is reliable, they are less likely to engage in non-farm activities. This means that non-farm activities are perhaps considered as an alternative means of securing income during agricultural off-seasons. It could also mean that non-farm income is likely to be re-invested into farm activities for renting in more farm land, purchasing inputs and oxen. In the long-run this may have a dynamic effect in creating capital that substitutes for labour, encouraging participation in non-farm activities (Reardon et al., 1998).

Our findings on the landholding partly re-affirms the farm/non-farm linkages (Reardon et al., 2000) and the dominant pattern consumption-driven non-farm income growth observed in some African countries such as Zambia (Hazell & Hojjati, 1995).

The fixed, random and instrumental variable estimations largely indicate that non-farm diversification seems to be pursued by wealthier households while poorer choose it only in case of shocks as a survival strategy. This result supports the increasingly strong empirical evidence that income diversification is being used as a means of accumulation in sub-Saharan Africa (see Block and Webb 2001; Barrett et al. 2001b; De Weerdt 2010; Dimova and Sen 2010).

In light of the findings of the positive roles of access to electricity and markets, it can be suggested that a more focused policy towards infrastructural development in rural areas can facilitate the transformation of the rural economy goals explicitly stated in the government's Growth and Transformation Plan (GTP) (FDRE, 2010). Increasing investments to promote access to electricity and roads could improve access to markets and remove some entry barriers for poorer households. This is crucial, as non-farm activities can remove some of the current pressure on farm land and reduce the rate of land degradation by providing alternative sources of income to smallholders in densely populated areas in Ethiopia. Enabling the poor to participate in non-farm activities also requires improving their asset base through creating alternative employment and income generating opportunities. Public work schemes can be play important role in this regard.

Moreover, accumulation being found to be the driving motive for non-farm diversification has implications for growing inequality in rural settings. Coupled with the entry-barriers to non-farm activities, this may indicate the existence of poverty and asset-traps. Thus, investigating further the effect of non-farm income on overall income inequality and welfare is an important research avenue, which is espoused as the major objective in the next paper.

## References

Abdulai, A., & CroleRees, A. (2001). Determinants of income diversification amongst rural households in Southern Mali. *Food Policy*, *26*(4), 437–452. doi:10.1016/S0306-9192(01)00013-6

Abdul-Hakim, R., & Che-Mat, S. H. (2011). Determinants of Farmer's Participation in Off-Farm Employment: A Case Study in Kedah Darul Aman, Malaysia. *Asian Journal of Agriculture and Rural Development*, *1*(2), 27–37.

Akaakohol, M. A., & Aye, G. C. (2014). Diversification and farm household welfare in Makurdi, Benue State, Nigeria. *Development Studies Research*, *1*(1), 168–175.

Allison, P. D. (2012). *Logistic regression using SAS: Theory and application*. SAS Institute.

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Aristei, D., & Pieroni, L. (2008). A double-hurdle approach to modelling tobacco consumption in Italy. *Applied Economics*, *40*(19), 2463–2476.

Atamanov, A., & Van Den Berg, M. (2011). *Microeconomic analysis of rural nonfarm activities in the Kyrgyz Republic: What determines participation and returns?* (The Maastricht Graduate School of Governance. Working Paper No. 2011WP001) (pp. 1–35). Maastricht: Maastricht University.

Babatunde, R. O., & Qaim, M. (2009). Patterns of income diversification in rural Nigeria: determinants and impacts. *Quarterly Journal of International Agriculture*, *48*(4), 305–320.

Bachewe, F. (2009). *The State of Subsistence Agriculture in Ethiopia: Sources of Output Growth and Agricultural Inefficiency* (PhD Dissertation). University of Minnesota.

Baltagi, B. (2008). *Econometric Analysis of Panel Data*. John Wiley & Sons.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331.

Berdegué, J. A., Ramírez, E., Reardon, T., & Escobar, G. (2001). Rural Nonfarm Employment and Incomes in Chile. *World Development*, *29*(3), 411–425. doi:10.1016/S0305-750X(00)00102-9

Bierens, H. (2004). The Tobit model. *Econometrica*, *26*, 24–36.

Block, S., & Webb, P. (2001). The dynamics of livelihood diversification in post-famine Ethiopia. *Food Policy*, *26*(4), 333–350. doi:10.1016/S0306-9192(01)00015-X

Burke, W. J. (2009). Fitting and interpreting Cragg's tobit alternative using Stata. *Stata Journal*, *9*(4), 584.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics Using Stata, Revised Edition*. Stata Press.

Canagarajah, S., Newman, C., & Bhattamishra, R. (2001). Non-farm income, gender, and inequality: evidence from rural Ghana and Uganda. *Food Policy*, *26*(4), 405–420.

Carlin, P., & Flood, L. (1997). Do Children Affect the Labor Supply of Swedish Men? Time Diary vs. Survey Data. *Labour Economics, 4*, 167–183.

Carswell, G. (2002). Livelihood diversification: increasing in importance or increasingly recognized? Evidence from southern Ethiopia. *Journal of International Development, 14*(6), 789–804. doi:10.1002/jid.924

Colman, D., & Young, T. (1997). *Principles of Agricultural Economics: Markets and Prices in Less Developed Countries*. Cambridge: Cambridge University Press.

Corral, L., & Reardon, T. (2001). Rural nonfarm incomes in Nicaragua. *World Development, 29*(3), 427–442. doi:10.1016/S0305-750X(00)00109-1

Cragg, J. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, *39*(5), 829–844.

Davis, J. R. (2003). The rural non-farm economy, livelihoods and their diversification: Issues and options. *NRI Report*, (2753).

Davis, J. R., & Bezemer, D. (2004). The development of the rural non-farm economy in developing countries and transition economies: key emerging and conceptual issues. *Available at SSRN 693061*.

Deaton, A., & Irish, M. (1984). Statistical models for zero expenditures in household budgets. *Journal of Public Economics, 23*, 59–80.

De Brauw, A., Mueller, V., & Woldehanna, T. (2013). Motives to remit: evidence from tracked internal migrants in Ethiopia. *World Development, 50*, 13–23.

Degefa, T. (2005). *Rural Livelihoods, Poverty and Food Insecurity in Ethiopia: A Case Study at Erenssa and Garbi Communities in Oromiya Zone, Amhara National Regional State*. Ntnu.

Demeke, M., & Regassa, T. (1996). Non-farm activities in Ethiopia: the case of North Shoa. Presented at the The Ethiopian Economy-Poverty and Poverty Alleviation:

Proceedings of the Fifth Annual Conference on the Ethiopian Economy, Addis Ababa.

Demissie, A., & Legesse, B. (2013). Determinants of income diversification among rural households: The case of smallholder farmers in Fedis district, Eastern hararghe zone, Ethiopia. *Journal of Development and Agricultural Economics*, *5*(3), 120–128.

Demissie, D., & Workneh, N. (2004). Determinants of Rural Livelihood Diversification: Evidence from south Ethiopia. *Quarterly Journal of International Agriculture*, *43*(3), 267–288.

Dercon, S., & Hoddinott, J. (2011). *The Ethiopian Rural Household Surveys 1989-2009: Introduction.* (University of Oxford and International Food Policy Research Institute(IFPRI)). Oxford.

Dercon, S., Hoddinott, J., & Woldehanna, T. (2012). Growth and Chronic Poverty: Evidence from Rural Communities in Ethiopia. *Journal of Development Studies*, *48*(2), 238–253. doi:10.1080/00220388.2011.625410

Dercon, S., & Krishnan, P. (1996). Income portfolios in rural Ethiopia and Tanzania: Choices and constraints. *Journal of Development Studies*, *32*(6), 850–875.

Deressa, T., Hassan, R. M., & Ringler, C. (2008). *Measuring Ethiopian farmers' vulnerability to climate change across regional states:* (Research briefs No. 15(5)). International Food Policy Research Institute (IFPRI). Retrieved from http://ideas.repec.org/p/fpr/resbrf/15(5).html

Deshingkar, P.(2004). *Livelihood Diversification in Developing Countries*. London: Organization for Economic Cooperation and Development.

De Weerdt, J. (2010). Moving out of poverty in Tanzania: Evidence from Kagera. *Journal of Development Studies*, *46*(2), 331–349.

Dimova, R., & Sen, K. (2010). *Is household income diversification a means of survival or a means of accumulation? Panel data evidence from Tanzania* (Brooks World Poverty Institute Working Paper Series No. 12210). BWPI, The University of Manchester. Retrieved from http://ideas.repec.org/p/bwp/bwppap/12210.html

Ellis, F. (1998). Household strategies and rural livelihood diversification. *Journal of Development Studies, 35*(1), 1–38. doi:10.1080/00220389808422553

Ellis, F. (2000). *Rural Livelihoods and Diversity in Developing Countries*. Oxford: Oxford University Press.

Ellis, F. (2004). *Occupational diversification in Developing Countries and the implications for agricultural policy*. Programme of Advisory and Support services to DFID. London: DFID.

Ellis, F., & Freeman, H. A. (Eds.). (2005). *Rural Livelihoods and Poverty Reduction Policies*. London and New York: Routledge.

Escobal, J. (2001). The Determinants of Nonfarm Income Diversification in Rural Peru. *World Development*, *29*(3), 497–508. doi:10.1016/S0305-750X(00)00104-2

Ezra, M., & Kiros, G.-E. (2001). Rural Out-migration in the Drought Prone Areas of Ethiopia: A Multilevel Analysis1. *International Migration Review*, *35*(3), 749–771.

FDRE (2010). *Growth and Transformation Plan:2010/11-2014/15, Vol.1, Main Text*. Addis Ababa: Ministry of Finance and Economic Development.

Fennema, J., & Sinning, M. (2007). Double-Hurdle Models with Dependent Errors and Heteroscedasticity. Essen.

Garcia, B. (2013). Implementation of a double-hurdle model. *The Stata Journal*, *13*(4), 776–794.

Gordon, A., & Craig, C. (2001). *Rural non-farm activities and poverty alleviation in sub-Saharan Africa* (No. 14). The University of Greenwich, London: The Natural Resources Institute (NRI).

Greene, W. (2005). Functional form and heterogeneity in models for count data. *Foundations and Trends in Econometrics*, *1*, 113–218.

Greene, W.(2008). Functional forms for the negative binomial model for count data. *Economics Letters*, *99*(3), 585–590.

Greene, W. H. (2000). *Econometric Analysis* (Fourth ed.). N.J: Prentice Hall: Englewood Cliffs.

Greene, W. H. (2008). *Econometric analysis*. Granite Hill Publishers.

Haggblade, S., Hazell, P. B. R., & Reardon, T. (Eds.). (2007). *Transforming the rural nonfarm economy: opportunities and threats in the developing world*. Johns Hopkins University Press.

Haggblade, S., Hazell, P., & Reardon, T. (2010). The Rural Non-farm Economy: Prospects for Growth and Poverty Reduction. *World Development*, *38*(10), 1429–1441. doi:10.1016/j.worlddev.2009.06.008

Hart, G. (1994). The dynamics of Diversification in an Asian Rice Region. In *Development or Deterioration?:Work in Rural Asia* (pp. 47–71). Boulder, Colorado: Lynne Reinner.

Hazell, P. B., & Hojjati, B. (1995). Farm/non-farm growth linkages in Zambia. *Journal of African Economies*, *4*(3), 406–435.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*, 153–161.

Idowu, A. O., Ojiako, I. A., & Ambali, O. I. (2013). Participation and Wage of Rural Female Headed Households in Nigeria's non-farm employment. *European Scientific Journal*, *9*(13).

Janvry, A. de, & Sadoulet, E. (2001). Income strategies among rural households in Mexico: The role of off-farm activities. *World Development*, *29*(3), 467–480.

Jones, A. M. (1992). A Note on Computation of the Double-Hurdle Model With Dependence With An Application to Tobacco Expenditure. *Bulletin of Economic Research*, *44*(1), 67–74.

Khatun, D., & Roy, B. (2012). Rural livelihood diversification in West Bengal: Determinants and constraints. *Agricultural Economics Research Review*, *25*(1), 115–124.

Kijima, Y., Matsumoto, T., & Yamano, T. (2006). Nonfarm employment, agricultural shocks, and poverty dynamics: evidence from rural Uganda. *Agricultural Economics*, *35*, 459–467. doi:10.1111/j.1574-0862.2006.00191.x

Kimsun, T., & Sokcheng, P. (2013). *The Role of Income Diversification during the Global Financial Crisis: Evidence from Nine Villages in Cambodia*. Working Paper Series.

Kuwornu, J. K. ., Bashiru, M., & Dumayiri, M. (2014). Farm Households' Livelihood Diversification into Agro-processing and Non-agro-processing Activities: Empirical Evidence from Ghana. *Information Management and Business Review*, *6*(4), 191–199.

Lanjouw, J. O., & Lanjouw, P. (2001). The rural non-farm sector: issues and evidence from developing countries. *Agricultural Economics*, *26*(1), 1–23.

Lanjouw, P., Shariff, A., & Rahut, D. B. (2007). *Rural Non-Farm Employment in India: Access, Income, Farm, Poverty Impact* (Working Paper No. id:913). eSocialSciences. Retrieved from http://ideas.repec.org/p/ess/wpaper/id913.html

Lemi, A. (2006). *The Dynamics of Income Diversification in Ethiopia: Evidence from Panel data* (Working Paper No. 3). University of Massachusetts Boston, Economics Department. Retrieved from http://ideas.repec.org/p/mab/wpaper/3.html

Lemi, A. (2010). Determinants of income diversification in rural Ethiopia: Evidence from panel data. *Ethiopian Journal of Economics*, *18*(1). doi:10.4314/eje.v18i1.59930

Loening, J., & Mikael Imru, L. (2009). Ethiopia: Diversifying the Rural Economy. An Assessment of the Investment Climate for Small and Informal Enterprises [MPRA Paper]. Retrieved May 25, 2014, from http://mpra.ub.uni-muenchen.de/23278/

Martinez-Espineira, R. (2006). A Box-Cox Double-Hurdle model of wildlife valuation: The citizen's perspective. *Ecological Economics*, *58*, 192–208.

Matshe, I., & Young, T. (2004). Off-farm labor allocation decisions in small-scale rural households in Zimbabwe. *Agricultural Economics*, *30*(2004), 175–186.

McClendon, M. J. (2002). *Multiple regression and causal analysis*. Waveland Press.

McDowell, A. (2003). From the help desk: hurdle models. *The Stata Journal*, *3*(2), 178–184.

Meert, H., Van Huylenbroeck, G., Vernimmen, T., Bourgeois, M., & van Hecke, E. (2005). Farm household survival strategies and diversification on marginal farms. *Journal of Rural Studies*, *21*(1), 81–97. doi:10.1016/j.jrurstud.2004.08.007

Mellor, J.(1963). The use and productivity of farm family labour in early stages of agricultural development. *Journal of Farm Economics*, *XLV*(3).

Minot, N. (2006). *Income diversification and poverty in the Northern Uplands of Vietnam* (Vol. 145). Intl Food Policy Res Inst.

Mogues, T. (2004). Shocks, livestock asset dynamics and social capital in Ethiopia. *University of Wisconsin-Madison, Mimeo*.

Mollers, J., & Buchenrieder, G. (2005). Theoretical Concepts for the Analysis of Non-farm Rural Employment. *Quarterly Journal of International Agriculture*, *44*(1), 19–36.

Newman, C., Henchion, M., & Matthews, A. (2001). Infrequency of purchase and double-hurdle models of Irish households' meat expenditure. *European Review of Agricultural Economics*, *28*(4), 393–419.

Newman, C., Henchion, M., & Matthews, A. (2003). A double-hurdle model of Irish household expenditure on prepared meals. *Applied Economics*, *35*(9), 1053–1061.

Olale, E., & Henson, S. (2012). Determinants of income diversification among fishing communities in Western Kenya. *Fisheries Research*, *125*, 235–242.

Olivia, S., & Gibson, J. (2008). The Effect of Infrastructure Access and Quality on Non-farm Employment and Income in Rural Indonesia. Presented at the 2009 Conference, August 16-22, 2009, Beijing, China, International Association of Agricultural Economists.

Pham, H. T., Tuan, B. A., Thanh, L., & Dao. (2010). *Is Nonfarm Diversification a way Out of Poverty for rural households? Evidence from Vietnam in 1993-2006* (SSRN Scholarly

Paper No. ID 1715603). Rochester, NY: Social Science Research Network. Retrieved from http://papers.ssrn.com/abstract=1715603.

Piza, E. (2012). *Using Poisson and Negative Binomial Regression Models to Measure the Influence of Risk on Crime Incident Counts*. Newark, NJ U.S.A.: Rutgers Center on Public Security. Retrieved from www.riskterainmodeling.com.

Pudney, S. (1989). *Modelling Individual Choice: The Econometrics of Corners, Kinks and Holes.* Massachusetts, MI: Blackwell Publishing.

Reardon, T. (1997). Using evidence of household income diversification to inform study of the rural nonfarm labor market in Africa. *World Development*, *25*(5), 735–747. doi:10.1016/S0305-750X(96)00137-4

Reardon, T., Berdegué, J., Barrett, C.,& Stamoulis, C. (2007). Household Income Diversification into Rural Nonfarm Activities. In Haggblade, S., Hazell, P. B. R., & Reardon, T. (Eds.). (2007). *Transforming the Rural Nonfarm Economy* (pp. 115–140). Baltimore: The John Hopkins University Press.

Reardon, T., Stamoulis, K., Balisacan, A., Cruz, M., Berdegué, J., & Banks, B. (1998a). Rural non-farm income in developing countries. *The State of Food and Agriculture, 1998*, 283–356.

Reardon, T., Stamoulis, K., Balisacan, A., Cruz, M., Berdegué, J., & Banks, B. (1998b). Rural non-farm income in developing countries. *The State of Food and Agriculture, 1998*, 283–356.

Reardon, T., Taylor, J. E., Stamoulis, K., Lanjouw, P., & Balisacan, A. (2000). Effects of non-farm employment on rural income inequality in developing countries: an investment perspective. *Journal of Agricultural Economics*, *51*(2), 266–288.

Renkow, M. (2007). 8 Cities, Towns, and the Rural Nonfarm Economy. *Transforming the Rural Nonfarm Economy: Opportunities and Threats in the Developing World*, 183.

Renkow, M., & Slade, R. (2013). *An assessment of IFPRI'S work in Ethiopia 1995–2010: Ideology, influence, and idiosyncrasy*. International Food Policy Research Institute.

Rijkers, B., Söderbom, M., & Teal, F. (2008). Rural non-farm enterprises in Ethiopia: Challenges and prospects. *Background Note Prepared for Study on Role of Agricultural Growth in Ethiopia*.

Ruben, R., & Van den berg, M. (2001). Nonfarm Employment and Poverty Alleviation of Rural Farm Households in Honduras. *World Development*, *29*(3), 549–560. doi:10.1016/S0305-750X(00)00107-8

Sabates-Wheeler, R., Mitchell, T., & Ellis, F. (2008). Avoiding Repetition: Time for CBA to Engage with the Livelihoods Literature? *IDS Bulletin*, *39*(4), 53–59. doi:10.1111/j.1759-5436.2008.tb00476.x

Sen, A. (1966). Peasants and dualism with or without surplus labour. *Journal of Political Economy*, *74*(5).

Senadza, B. (2012). Non-farm Income Diversification in Rural Ghana: Patterns and Determinants. *African Development Review*, *24*(3), 233–244. doi:10.1111/j.1467-8268.2012.00322.x

Sharp, K., Devereux, S., & Amare, Y. (2003). *Destitution in Ethiopia's Northeastern highlands (Amhara National Regional State)*. Institute of Development Studies at the University of Sussex.

Smith, D. A., & Brame, R. (2003). Tobit Models in Social Science Research Some Limitations and a More General Alternative. *Sociological Methods & Research*, *31*(3), 364–388.

Smith, D. R., Gordon, A., Meadows, K., & Zwick, K. (2001). Livelihood diversification in Uganda: patterns and determinants of change across two rural districts. *Food Policy*, *26*(4), 421–435. doi:10.1016/S0306-9192(01)00012-4

Sosina, B., & Holden, S. (2014). Are Rural Youth in Ethiopia Abandoning Agriculture? *World Development*, *64*, 259–272. doi:10.1016/j.worlddev.2014.06.013

Sosina, B., & Barrett, C. (2012). Employment Dynamics in the Rural Nonfarm Sector in Ethiopia: Do the Poor Have Time on Their Side? *Journal of Development Studies*, *48*(9), 1223–1240. doi:10.1080/00220388.2012.671476

Sosina, B., Barrett, C. B., & Holden, S. T. (2012). Does the Nonfarm Economy Offer Pathways for Upward Mobility? Evidence from a Panel Data Study in Ethiopia. *World Development*, *40*(8), 1634–1646.

Start, D. (2001). The Rise and Fall of the Rural Non-farm Economy: Poverty Impacts and Policy Options. *Development Policy Review*, *19*(4), 491–505. doi:10.1111/1467-7679.00147

Taylor, J. E., & Yunez-Naude, A. (2000). The returns from schooling in a diversified rural economy. *American Journal of Agricultural Economics*, *82*(2), 287–297.

Tegegne, G. (2000). *Non-farm Activities and Production Decisions of Farmers: the Case of Damotgale and Kachabira Woredas, in south Regions of Ethiopia* (Social Science Research Report Series No. 15). Addis Ababa: OSSREA.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica*, *26*(1), 24–36.

Woldenhanna, T., & Oskam, A. (2001). Income diversification and entry barriers: evidence from the Tigray region of northern Ethiopia. *Food Policy*, *26*(4), 351–365.

Wooldridge, J. (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wooldridge, J. (2008). *Introductory Econometrics: A Modern Approach*. Cengage Learning.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

World Bank. (2009). *Ethiopia: Diversifying the Rural Economy. An Assessment of the Investment Climate for Small and Informal Enterprises* (MPRA Paper). Retrieved from http://mpra.ub.uni-muenchen.de/23278/

Yared, A. (1999). *Household resources, strategies and food security in Ethiopia: a study of Amhara households in Wogda, Northern Shewa*. Addis Ababa: Addis Ababa University Press.

Yen, S. T., & Jensen, H. H. (1996). Determinants of household expenditures on alcohol. *Journal of Consumer Affairs*, *30*(1), 48–67.

Yen, S. T., & Jones, A. M. (1997). Household consumption of cheese: an inverse hyperbolic sine double-hurdle model with dependent errors. *American Journal of Agricultural Economics*, *79*(1), 246–251.

Yúnez-Naude, A., & Edward Taylor, J. (2001). The Determinants of Nonfarm Activities and Incomes of Rural Households in Mexico, with Emphasis on Education. *World Development*, *29*(3), 561–572. doi:10.1016/S0305-750X(00)00108-X

Yunez-Naude, A., & Edward Taylor, J. (2001). The determinants of nonfarm activities and incomes of rural households in Mexico, with emphasis on education. *World Development*, *29*(3), 561–572.

## Annex

**Figure 1: Histogram of the number of non-farm activity distribution**

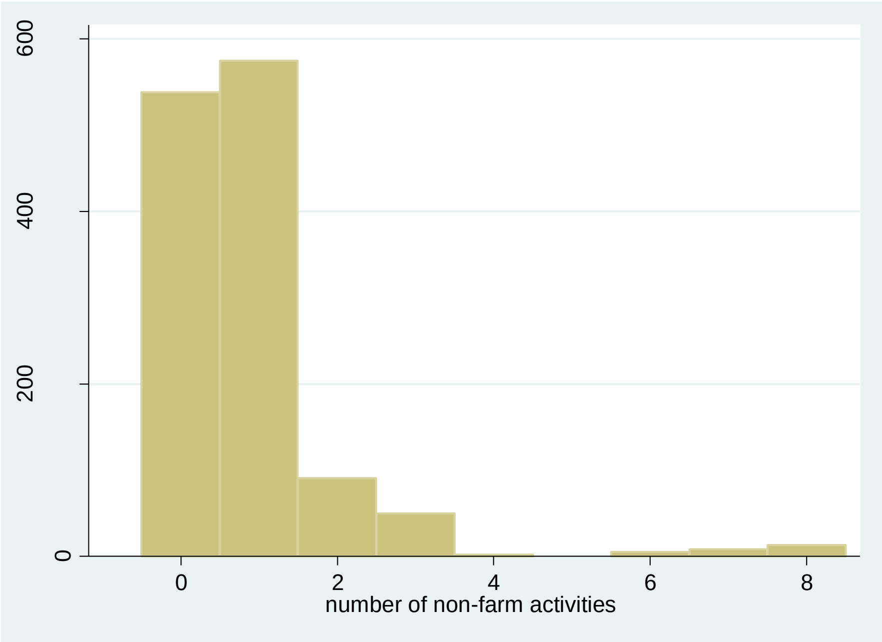
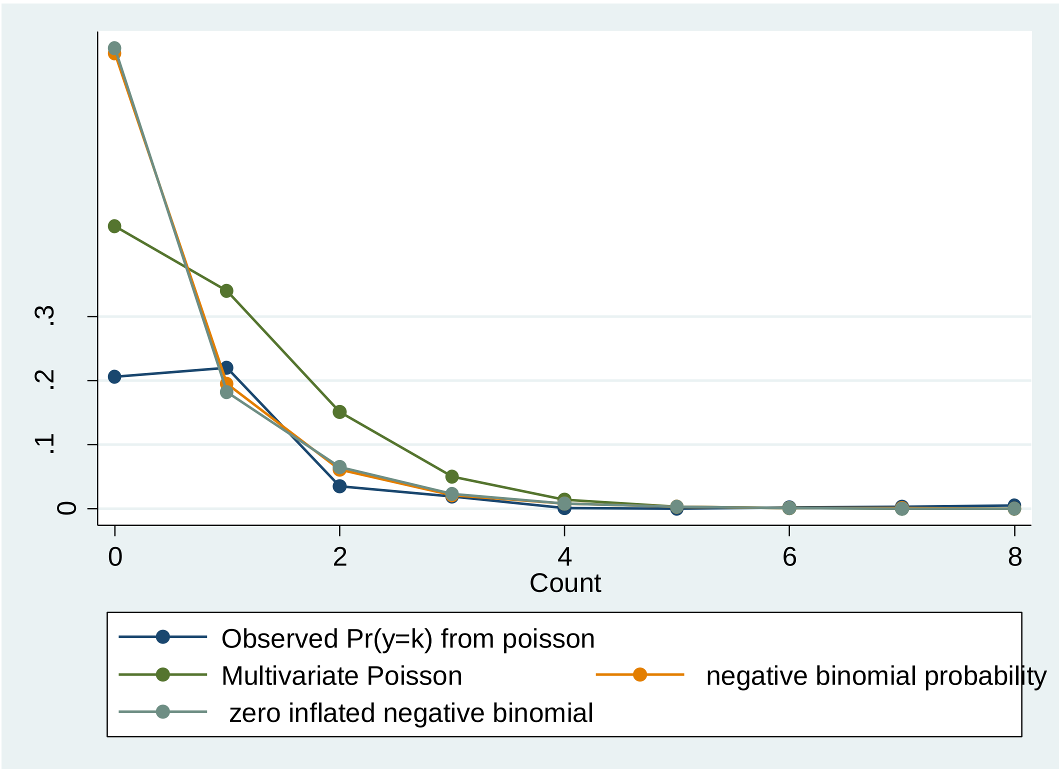



**Figure 2: Observed distribution of non-farm activities**




*Note*

The Poisson model doesn't fit well with the observed counts as it under predicts zeros and over predicts ones and twos. The NBM and the ZINB models are better in fitting the data.

**Table A: Pearson goodness-of-fit test result for non-farm activities**

| ystar | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| muhat | 1.683078 | .3154693 | 5.34 | 0.000 | 1.064391 | 2.301765 |

*Note:*
The test shows that number of non-farm activities is over-dispersed

**A goodness-of-fit test for the Poisson Model**

Deviance goodness-of-fit = 2233.921
Prob > chi2(1961) = 0.0000

Pearson goodness-of-fit = 3658.821
Prob > chi2(1961) = 0.0000

Goodness-of-fit chi2 = 3658.821
Prob > chi2(1961) = 0.0000

Since the probability is below .05, the predicted counts are significantly different from the observed ones, and therefore Poisson model doesn't fit well for the data.

**Table B: Tobit, Probit, and Truncated Regression models of non-farm income determinants**

| | Tobit estimates* | Probit regression | Truncated regression |
|---|---|---|---|
| Age of the household head | $0.0172^{*}$ | 0.00427 | $0.00576^{*}$ |
| | (0.00667) | (0.00226) | (0.00263) |
| Household head is male (=1) | $-0.616^{**}$ | $-0.377^{***}$ | $-0.168^{*}$ |
| | (0.204) | (0.0674) | (0.0798) |
| Education (years of schooling) | $0.150^{***}$ | $0.0270^{*}$ | $0.0398^{**}$ |
| | (0.0342) | (0.0117) | (0.0132) |
| Household size | 0.00377 | | $0.0720^{***}$ |
| | (0.0382) | | (0.0152) |
| Dependency ratio | | 0.108 | |
| | | (0.136) | |
| Livestock holding (tlu) | $-0.0708^{**}$ | | 0.00425 |
| | (0.0239) | | (0.00967) |
| Access to credit (=1) | 0.183 | 0.0602 | 0.0853 |
| | (0.187) | (0.0622) | (0.0746) |
| Landholding ( in ha) | $-0.349^{***}$ | | 0.0118 |
| | (0.0870) | | (0.0364) |
| Asset index | 0.577 | | 0.454 |
| | (0.787) | | (0.342) |
| Ln crop income | $-0.344^{***}$ | | -0.0132 |
| | (0.0558) | | (0.0205) |
| Climate shock index | 0.0715 | $0.135^{*}$ | $-0.276^{***}$ |
| | (0.194) | (0.0640) | (0.0777) |
| Death of a working member (=1) | -0.301 | -0.0821 | -0.110 |
| | (0.226) | (0.0748) | (0.0908) |
| Illness dummy (=1) | $0.573^{**}$ | $0.237^{***}$ | $0.171^{*}$ |
| | (0.182) | (0.0606) | (0.0721) |
| Access to electricity (=1) | $0.963^{***}$ | $0.398^{***}$ | 0.0335 |
| | (0.193) | (0.0657) | (0.0760) |
| Distance to nearest town ( in kms) | -0.0240 | -0.00456 | 0.0101 |
| | (0.0186) | (0.00595) | (0.00747) |
| _se | $3.768^{***}$ | | |
| | (0.0800) | | |
| _cons | $4.736^{***}$ | 0.107 | $5.007^{***}$ |
| | (0.638) | (0.173) | (0.247) |
| sigma | | | |
| _cons | | | $1.280^{***}$ |
| | | | (0.0247) |
| *N* | 1977 | 2013 | 1348 |
| chi2 | 217.4 | 112.4 | 66.12 |
| ll | -4298.8 | -1200.2 | -2245.7 |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes:*
The LR test statistics is -2*( ltobit-(lprobit+ ltrunc))= 1705.8
* The restricted model is tobit. The unrestricted more flexible model is the two-part model. Here the test statistic is large enough; we will reject the null that the restrictive tobit model is valid.

The $\chi^2$ (15) = 1705.8, this is less than the critical value 25. Thus, the two-part model is a better fit than the tobit model.

**Table C: Specification tests for Tobit and Double-Hurdle models**

| Model | Test value | Decision |
|---|---|---|
| Heckman selection model vs Tobit model | 1870.023(18)*** | Reject Heckman and accept Tobit |
| Test for Tobit vs Probit and truncated regression | 1705.8 (15)*** | Reject Tobit and accept the two-step model (Cregg or double-hurdle models) |

Source: computed from ERHS 2004–2009.

*Notes:*
The degrees of freedom of the chi-square statistics are given in parentheses.

***, **, * denote significance level at the 1 %, 5 % and 10 %.

**Table D: Summary Statistics of key variables used in the estimations (1994–2009)**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Age of household head | 4917 | 48.97 | 15.14 | 15 | 89 |
| Male head(=1) | 4960 | .74 | .4396 | 0 | 1 |
| Highest grade completed | 4810 | 3.27 | 3.575 | 0 | 16 |
| Dependency ratio | 4922 | .48 | .2137 | 0 | 1 |
| Household size | 4960 | 6.41 | 2.93 | 1 | 31 |
| Livestock holding (tlu) | 4918 | 3.45 | 4.161 | 0 | 61.85 |
| Land size (ha) | 4840 | 1.19 | 1.357 | 0 | 16.25 |
| Land quality index | 4488 | 2.21 | 1.43 | 1 | 9 |
| Credit access dummy | 4936 | .503 | .4968 | 0 | 1 |
| Ln of asset value | 4960 | 5.25 | 1.402 | 0.29 | 10.99 |
| Ln Annual crop income | 4548 | 6.896 | 1.316 | 0.40 | 11.27 |
| Ln non-farm income | 2261 | 5.632 | 1.407 | 0.68 | 10.76 |
| Asset index | 4820 | 0.312 | .3512 | -2.72 | 1.056 |
| Perennial crop production | 4960 | .575 | .4943 | 0 | 1 |
| Death of a working member | 4888 | .24 | .427 | 0 | 1 |

Source: computed from ERHS dataset

*Notes:*

Dependency ratio is defined as ratio of family members below age 15 and above age 60 to total family size.

Poor is a dummy variable determined by using the Poverty line of 50 Birr/adult equivalents per month in 1994 prices. This poverty line has been used by various authors and calculated from a food poverty line (constructed using a bundle of food items that would provide 2300 Kcal per adult per day) and a non-food bundle using the method employed by Ravallion and Bidani (1994) (cited in Dercon et al. 2011). Poverty in the sample surveys is high (Porter 2012) increasing from 47.3 % in 1994 to 53% in 2009. During the survey years especially between the two recent rounds, households faced high inflation especially on food prices.

Average Land Quality Index is a composite variable that takes both slope and nutrient content of the soil into consideration. It is calculated by multiplying the two indicators .Thus, for example if a land has a flat slope, it is assigned a value of 1 and if it is rich in its mineral content it is given similar value of 1. Similarly, land with high slope and poor nutrients gets 3*3=9.

Loan taken dummy refers to a yes or no response to the survey question “have you ever taken out a loan of at least 20 Birr?” This doesn’t necessarily indicate access to formal credit institution.

Asset Index this is constructed using the Principal Component Analysis (PCA) method. It is meant to show the permanent (durable) resources available to the household.

**Table E: Likelihood Ratio tests for Homoscedastic versus Heteroscedastic DHM**

| | Model 1 | Model 2 |
|---|---|---|
| Restricted (H0): Double Hurdle Log-likelihood | -3431.62 | -3438.02 |
| Unrestricted (H1): Hetero Double Hurdle Log-likelihood | -3367.40 | -3367.40 |
| Test statistic | 128.45 | 141.24 |
| Critical value 5% | 5.99 | 9.48 |
| P-value | 0.000 | 0.000 |

*Notes:*

Model 1: The Ln of consumption per capita and Ln of annual crop income are excluded from the restricted model
Model 2: The Ln of consumption per capita, Ln of annual crop income, size of land holding, and asset index are excluded.
The exclusion restrictions were imposed following the approach suggested by Yen & Jensen (1996), Newman et al. (2003) and Aristei and Pieroni (2008).

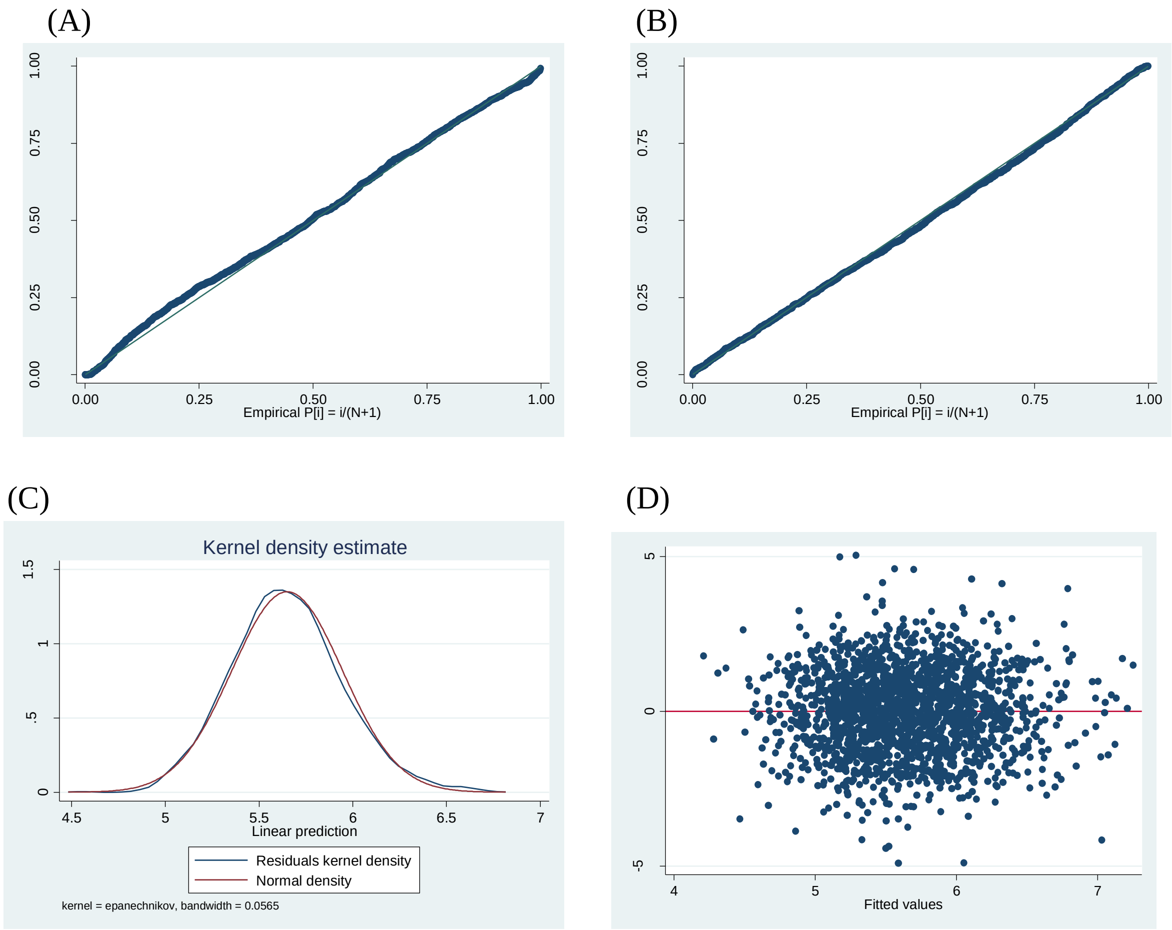



**Figure 3: Double-hurdle model: Checking assumptions with graphical plots**

(A) Standardized normal probability plot of residuals for Tier-1

(B) Standardized normal probability plot of residuals for Tier-2

(C) Kernel density estimate of residuals

(D) Plot of residuals against predicted values

# Essay 3

## Non-farm Diversification, Income inequality and Poverty in Rural Ethiopia


**Abstract**

This paper investigates whether non-farm income diversification increases or decreases overall income inequality and the likelihood of poverty in rural Ethiopia using a four-wave panel data from the Ethiopian Rural Household Survey over the period 1994–2009.The impacts of non-farm income on inequality and poverty are analyzed using Gini-coefficient decomposition, fixed and random, and probit models respectively. The analysis reveals that in general, non-farm income has an inequality reducing effect. The fixed, random and probit models also show that non-farm diversification has a positive impact on rural households' welfare. These results have important policy implications and suggest that the non-farm sector in rural Ethiopia can provide a feasible option to tackling rural poverty and vulnerabilities at a time when agriculture is increasingly becoming precarious due to the changing climate.



Keywords: non-farm diversification; inequality; Gini-decomposition; rural Ethiopia

JEL codes: I32, Q12 D63

## 1. Introduction

There are two broad views about livelihood diversification in sub-Saharan Africa. These views are largely expressed by 'agriculture optimists' and 'agriculture skeptics' (see Ellis, 2005:1-2). Agriculture optimists argue that African agriculture is dominated by smallholders and it is possible to increase their productivity and achieve the goals of raising income and food security (Gollin, Parente, & Rogerson, 2002; World Bank, 2007; Byerlee, De Janvry, & Sadoulet, 2009). Some writers in this camp view non-agricultural alternatives such as the non-farm sector in Africa as dominated by informal, risky and low-remunerative activities and has low impact on reducing poverty (Thirtle et al., 2001 cited in Tubiana, 2012).

On the other hand, the agricultural skeptics view livelihood diversification as a manifestation of the failure of agriculture to generate sufficient and secure livelihoods in Africa and argue that diversification out of the agricultural sector is needed to create employment and income opportunities (Ashley & Maxwell, 2001; Ellis, 2005). Some even consider supporting smallholder agriculture as inefficient use of resources and incompatible with economic development since the sector offers little opportunity for supporting decent livelihoods (Collier, 2008). Ellis (2005; 2007) also argues that agricultural optimist strategies such as the Agricultural Development Led Industrialisation (ADLI) strategy in Ethiopia failed in its attempt to increase smallholder productivity and instead "trapped" people in unproductive agriculture.[39]

This paper broadly subscribes to the agricultural skeptics' argument and views non-farm diversification as largely having a positive outcome for rural livelihoods as risk-managing as

[39] From the late 1990s Ethiopia followed an "agriculture first" policy with a focus on smallholder agriculture. This has changed recently with the launching of the Growth and Transformation Plan (GTP) that gives equal attention to stimulating growth in the non-agricultural sectors.

well as an accumulation strategy. However, following Barrett, Reardon, & Webb (2001) it argues that depending on the underlying motives and determining factors, non-farm diversification have different implications for reducing poverty and rural inequality. For example, the existence of entry barriers indicates that the benefits of non-farm diversification could largely accrue to the rich rather than the poor (Nega, Marysse, Tollens, & Mathijs, 2009). This in turn raises the question whether diversifying into non-farm activities has any impact on reducing poverty and inequality. In this paper, the impact of non-farm diversification on poverty and inequality is investigated using a panel data from rural Ethiopia.

## 2. Literature Review

There is an extensive literature on diversification and its impacts on household welfare and poverty (Webb & Reardon;1992; Reardon et al., 2000; De Janvry, Sadoulet, & Zhu, 2005; Van Den Berg & Kumbi, 2006; Kijima, Matsumoto, & Yamano, 2006; Abdul-Hakim & Che-Mat, 2011; Himanshu et al., 2013; Akaakohol & Aye, 2014; Scharf & Rahut, 2014). In both the theoretical and empirical literature the positive impacts of diversification are emphasized and are said to include consumption smoothing, risk reduction, more complete use of available household labor and skills, cash generation for investment in human or physical capital. Thus, by reducing the risk of income failure confronted by a household, diversification can help to maintain a household's consumption especially during harvest failures in rain-fed agriculture. In this regard, Webb and Reardon (1992) in their study of drought impact and household responses in East and West Africa note that diversification may simply achieve higher income than is possible by specializing in the *single occupation of farming* (emphasis added). According to them, the capacity of households in Burkina Faso to cope with drought shocks is strongly associated with the extent of their non-farm diversification pattern. Thus, when crops fail or livestock die, households are forced to reallocate labour to other pursuits, whether employment in off-farm (e.g. agricultural wage labor), or non-farm activities (e.g. weaving, brewing and petty-trade). This may suggest that diversification can play an important role at household level in achieving the objectives of reducing vulnerability and raising income (Webb & Reardon; 1992).

In the following paragraphs, studies that specifically focus on the effect of non-farm diversification on poverty and inequality in Asia, Africa and Ethiopia are reviewed in respective order.

With regards to Latin America, several studies show that the non-farm sector is fast-growing and has a poverty alleviating effect in the region ( Berdegué et al, 2001; Deininger & Olinto, 2001; Escobal, 2001; Ferreira & Lanjouw, 2001; Ruben and Van Den Berg, 2001). Reardon et al. (2001) summarized these and other rural household income studies from 11 Latin America countries that have used data from 1990s to show that the rural non-farm income is about 40 % of total rural incomes in the region.

However, the Latin American studies may paint a different picture from the empirical studies from South Asia and Sub-Saharan Africa that are reviewed in this study. This is because the region has the least rural population share in the world (see World Bank, 2013)[40] and except for Haiti most countries have reached middle income status. Thus, any reduction in poverty due to the non-farm sector is likely to be located in urban centres and associated with expansion of the manufacturing sector rather than being undertaken by rural households.

[40] According to the World Bank's figures, the rural population share for Latin America and the Caribbean is 21% in 2013. This figure is much lower than South Asia's (68%) and Sub-Saharan Africa's (63%) and makes Latin America a highly urbanized region not only among the developing regions but also more than other regions such as the Euro area (see World Bank, 2013).

Moreover, agricultural production in many countries of Latin America is organized differently than in Africa or South Asia as it is marked by the prevalence of large landlord estates, or *Latifundia* that has implications for income inequality and welfare (see Conning, 2003). Regardless of this, we have choose to review a few Latin American studies that have similarities with the context of smallholder agriculture system in Sub-Saharan Africa while at the same time highlighting the peculiarities of the region as discussed above.

Ferreira & Lanjouw (2001) studied non-farm activities in relation to poverty profile in Northeast Brazil applying a probit model on two data sets from 1996 with 6589 rural residents. They found that non-farm diversification complements the budgets of the poor and serves as a way of self-insuring against shocks. Moreover, non-farm enterprise income shares are strongly related to growth in per capita consumption than wage labour.

Lazarte-Alcala et al. (2012) used data from the Measurement of Living Conditions in Latin America and the Caribbean (MECOVI), for the period 1999-2002 to study remittances and income diversification in Bolivia's Rural Sector. Using binary endogenous variable model on a sample of 2,108 rural households, they found that for the small poor farmers located mainly in the Altiplano region in the west, who practice subsistence farming, the receipt of remittances (part of non-farm income) largely supports consumption. In the other regions, however, the existence of a capitalist farming sector, oriented to the domestic and foreign markets offers alternative sources of income and remittances are being used as a source of liquidity.

### *Studies from Asia*

Adams (1994) uses a three-year panel data and decomposition analysis to study the impact of non-farm income on overall income inequality in rural Pakistan. The study finds that non-farm income largely signifies an inequality-decreasing source of income. Importantly, the study also indicates that the components of non-farm income can have different effects on inequality. For instance, unskilled labour income has the most equalising effect on income distribution, while non-farm government income reveals a dis-equalizing effect.

De Janvry et al. (2005) studied the role of non-farm income on reducing rural poverty and inequality in china using data collected from Habei province on 7,333 households. The results from counterfactual and two-step Heckman procedures show that non-farm activities and income positively relate to farm production and enhance investment in the farm activities. Their results also indicate that non-farm activities have inequality and poverty reducing effects.

Another study from china by Zhu & Luo (2005) on the distribution of non-farm income in rural China using Gini index decomposition also find that non-farm activities reduced rural income inequality. Their study used data from the Living Standards Measurement Surveys for the years 1995 and 1997 consisting a sample of 787 rural households from two provinces.

A study from Malaysia by Abdul-Hakim and Che-Mat (2011) examines if farmers' diversification into non-farm activities reduce the likelihood of poverty. Based on a survey of 384 households and estimating a logit model, they find that non-farm employment has decreases the probability of a household being poor.

Himanshu et al. (2013) based on a combination of national data on the non-farm sector in India from early 1980s to late 2000s and village surveys find that non-farm diversification is increasingly pro-poor. Their village level analysis also show the non-farm sector is reducing poverty while at the same time significantly increasing income inequality.

Finally, a recent study by Scharf and Rahut (2014) investigate the well-being and distributional effects of non-farm employment using a survey collected from 520 rural households in the Himalayas, west Bengal, India. With a system of structural equations and instrumental variable regressions they find that low-return nonfarm employment is associated with lower income inequality, while high-return nonfarm activities have a dis-equalizing effect on income distribution.

***Studies from Africa***

Adams (1999) examines the impact of five sources of income, including non-farm income, on rural income inequality in Rural Egypt using gini-coefficient decomposition. The results show that nonfarm income is highly important for the rural poor in Egypt as it accounts for almost 60% of their total per capita income and reduces income inequality. However, not all sources of nonfarm income have equal impact on income distribution. Thus, unskilled labour represents an important inequality-decreasing source of rural income.

Canagarajah, et al. (2001) using data from Ghana and Uganda find that non-farm earnings contribute to rising inequality, but that lower income groups also benefit due to strong overall growth in non-farm earnings. Self-employment income has inequality-increasing effect while wage income reduces inequality. They also find that among female-headed households, self-employment is important than wage employment.

Using panel data from 894 rural Ugandan households in 2003 and 2005, Kijima et al. (2006) examined the role of non-farm employment in poverty reduction. Their findings indicate that asset-poor households tend to increase supply of labour to low-return activities to respond to idiosyncratic shocks while the non-poor engage in self-employed business thereby increasing the income inequality.

Olugbire et al. (2011) investigate the impact of non-farm employment on household income and poverty in Nigeria. They used propensity score matching approach to evaluate the differences in income using participation in non-farm activities as a treatment variable. Their results show that non-farm wage-employment has a higher impact on welfare than non-farm self-employment.

***Studies from Ethiopia***

A study by Block and Webb (2001) based on a survey of 300 households from rural Ethiopia find that wealthier households tend to have more diversified income sources. Moreover, those with more diversified incomes also had a greater increase in both income and calorie intake. This highlights that differential access to non-farm income is likely to have inequality increasing effect.

Van Den Berg & Kumbi (2006) analyse the relation between non-farm income, poverty, and inequality in Oromia region, Ethiopia. They use econometric estimates of household income from the nonfarm sector and gini-decomposition of income inequality by source for a sample of 1,704 households. They find that entry barriers to non-farm activities in the region are low, and growth in the non-farm sector is favourable to the poor.

Nega et al. (2009) studies income diversification, social capital and the level of inequality using a micro level data from 385 rural households in Tigray, Northern Ethiopia. His findings highlight that non-farm income generally has an inequality increasing effect due of barriers to entry. Moreover, certain type of activities within the non-farm sector mainly own business, and wage income are found to have un-equalizing effect.

Sosina and Barrett (2012) explore rural employment transitions in Ethiopia between farm and non-farm employment and find that initial asset holdings and access to saving and credit are important factors for transition into high-return rural non-farm employment. These factors are likely to act as entry barriers and have inequality inducing effects.

In another study Sosina, Barrett and Holden (2012) examine whether nonfarm employment leads to higher consumption expenditure growth in Ethiopia using the Ethiopian Rural Household Survey (ERHS) data for the years 1994, 1999 and 2004.Their findings indicate that households' consumption expenditure growth has a positive correlation with the initial share of nonfarm income; for wealthier households, the growth elasticity of nonfarm income share is higher; and human and physical capital contribute to higher rates of return for nonfarm participants.

In sum, the empirical evidences from Asia mostly show that non-farm income has a poverty and inequality reducing effect. It also demonstrates the merits of disaggregating non-farm income/activities to enhance our understanding of non-farm diversification's effect on welfare. The studies from Africa, on the other hand, largely seem to indicate that non-farm income has an inequality-inducing effect. Most of these studies used gini-coefficient decomposition and highlight that the self-employment part of the non-farm income has a much greater effect in increasing inequality. This in turn seems to reflect the lack of non-farm income generating opportunities in rural Africa and the existence of substantial entry barriers that make the relatively wealthy farm households to dominate the lucrative self-employment activities.

The studies from rural Ethiopia give mixed evidence with regards to the relationship between non-farm income, poverty and inequality. Some regional studies indicate that the non-farm sector is favourable to the poor having low entry barriers for participation (see Van Den Berg & Kumbi, 2006) while others show that non-farm diversification is constrained by considerable entry barriers which disproportionally affects the poor and therefore increases the income inequality (Block and Webb, 2001; Woldenhanna & Oskam, 2001). Moreover, the evidence is not clear and conclusive as to whether non-farm income increases or decreases the likelihood of poverty.

Thus, this paper aims to fill this gap by examining the impact of non-farm income on poverty and assess its distributional effect. In doing so, it looks into specific components of the non-farm diversification as the welfare and distributional impact of non-farm income depends on the specific type of non-farm activities and the capacities of households to access these activities as highlighted in the literature (De Janvry et al., 2005).

### 3. Data and Methods

The data used in this study comes from the Ethiopian Rural Household Survey (ERHS) for the period 1994–2009.[41] It is a panel household survey that includes 1,477 households in 15 districts of rural Ethiopia. The surveys cover four major regions (Amhara, Tigray, Oromya and South) where the country's largest proportion of settled farmers are found. In this paper, data from the four rounds of surveys from the years (1994, 1997, 2004 and 2009) are used consisting of a total of 1,240 households. Although the information contained in these surveys is fairly consistent, there are modules present in the 2004 and 2009 rounds that are not included in previous surveys. These modules mainly include questions about shocks and public works and the results of from our analysis could be limited by their absence.

The data show that consumption per capita growth between 1994 and 1997 rounds was very strong (Dercon, Hoddinott, & Woldehanna, 2012). This seems to have some effect on reduction of poverty from 47 percent in 1994 to 33 percent in 1997 (see Table 1). However, this reduction in poverty rate reversed between 1997 and 2004 partly due to the 2002/03 drought that affected 13.2 million people (it has been considered the worst drought since 1984 – De Waal, Seyoum Taffesse, & Carruth, 2006). Between the latest survey rounds (2004 and 2009), another fundamental change that shaped the rural economy was the high food-price inflation which occurred both before and after 2004 (Uregia, Desta, & Rashid, 2012).

[41] The data were collected by the Economics Department of Addis Ababa University (AAU), the Centre for the Study of African Economies (CSAE), University of Oxford and the International Food Policy Research Institute (IFPRI).

In terms of overall income diversification measure, the households in the ERHS sample have increased their diversification index, as measured as a reverse of the Herfindal index of income concentration (see Figure 1, annex).

**Table 1: Consumption and Poverty Indices, 1994-2009**

| Year | Mean Consumption per capita | Median Consumption per capita | poverty Head count | Poverty Gap | Squared Poverty Gap |
|---|---|---|---|---|---|
| 1994 | 70.37 | 51.86 | 47.50 | 0.2084 | 0.1181 |
| 1997 | 87.65 | 70.38 | 33.14 | 0.1158 | 0.0566 |
| 2004 | 91.43 | 64.69 | 35.73 | 0.1304 | 0.0667 |
| 2009 | 58.80 | 47.36 | 52.78 | 0.2093 | 0.1111 |

Source: computed from the ERHS.

*Note:*
The poverty head count is determined by using the Poverty line of 50 Birr/adult equivalents per month in 1994 prices.

For the purpose of this paper, income was categorized into three major parts: farm, non-farm, and off-farm income. Following the main distinction made in the literature, the non-farm income is divided into two sub-categories– non-farm self-employment income and non-farm wage income. Farm income refers to the sum of the income earned from crop production converted to monetary value including value of crop residue, income from the sale of animal products, and income earned from the sale of livestock (excluding distress sales). Non-farm income aggregates a range of activities that span from regular salaried work to self-employed activities such as trading. Moreover, income earned from renting land and oxen (rent income) as well as remittances are categorized as non-farm income. A full list of these activities and their composition is provided in Figure 2 (Annexed).

## Methods

This paper investigates the effect of non-farm income on poverty and inequality using two methods (1) Gini-decomposition of income inequality by income sources and (2) Econometric estimation of welfare/poverty as a function of household and community characteristics. Following Van De Walle and Cratty (2004), the probability of being poor (if consumption per capita, is less than the poverty line) is used as a binary response dependent variable.

### 3.1. Decomposition of Income Inequality by Income Source

The Gini coefficient decomposition technique is often used to analyse income inequality and have been applied extensively to examine the effect of non-farm diversification on income inequality (Adams, 1999; Zhu & Luo, 2005).

Suppose that $y_1$, $y_2$...., $y_k$ stand for $k$ components of household income and $y_0$ the total income, $y_0 = \sum_{k=1}^{K} y_k$

Following Lerman and Yitzhaki (1985) the Gini index of the total income, $G$ can be given as:

$$G = \sum_{k=1}^{K} R_k G_k S_k \tag{1}$$

where:

$S_k$ is the share of income from source $k$ in total group income

$G_k$ is the Gini-coefficient of income inequality for income from source $k$ or the pseudo-Gini coefficient of an income source;

$R_k$ the correlation between income source $k$ income and the distribution of total income $R_k$ can be defined as:

$$R_k = \frac{\operatorname{cov}[Y_{k,} F(Y)]}{\operatorname{cov}[Y_{k,} F(Y_k)]} \qquad (2)$$

where $Cov[Y_k, F(Y)]$, is the covariance between source income amount and total income rank This method of Gini-decomposition can be used to determine the contribution of a particular income source to total income inequality by estimating the effect that a 1% change in income from source *k* on total income inequality (Feldman, 2009). This effect is given by:

$$\frac{S_k G_k R_k}{G} - S_k \qquad (3)$$

### 3.2. Econometric estimations

If $Y_{it}$ is per capita consumption for household *i* at time *t*, then $Y_{it}$ can be defined as a function of non-farm income diversification ($Nd_{it}$) and other explanatory variables $X_{it}$, which can be stated as

$$Y_{it} = \alpha Nd_{it} + \boldsymbol{\beta X}_{it} + \boldsymbol{\mu_i} + \boldsymbol{\varepsilon_{it}} \qquad (3)$$

Where *X* represents household characteristics such as gender, age, education, household size, size of farm land, asset index, livestock holding, land quality index and access to credit; $\mu_i$ captures unobserved effects, $\varepsilon_i$ is a random error term; and $\alpha$, and $\boldsymbol{\beta}$ are the parameters to be estimated.

This paper uses a random effects probit model to examine the relationship between the likelihood of poverty and non-farm diversification.[42]

[42] A conditional fixed-effects estimate does not exist as there is no sufficient statistic to permit the fixed effects to be conditioned out of the likelihood. Unconditional fixed-effects can be estimated using indicator variables for the panels but such effects are likely to be biased (Wooldridge, 2010). The results of the probit estimates are compared to fixed and logit estimations. The Hausman test favours the FE logit over the RE. The results of the FE estimations have the expected sign for the ln non-farm income, but do not have a statistical significance. The Akaike's information criterion (AIC) and Bayesian information criterion (BIC) for model comparison were also attempted to choose between the different models. However, this test is not valid since the number of observations used in the estimations differs since time-invariant regressors are dropped from the fixed-effects logit model. Thus, we instead used the test to choose between the random-effects logit model vs. the random-effects probit and choose the later since it has a slightly less AIC and BIC.

The standard unobserved effects probit model's main assumption can be expressed by following (Wooldridge, 2002) as:

$$P(y_{it} = 1|\boldsymbol{X_i}, u_i) = P(y_{it} = 1|\boldsymbol{X_{it}}, u_i) = \Phi(\boldsymbol{X_{it}\beta} + u_i), \qquad t = 1,....T \tag{4}$$

where $u_i$ is the unobserved effect and $X_i$ contains $X_{it}$ for all t. The first equality indicates that $X_{it}$ is strictly exogenous conditional on $u_i$: once $u_i$ is conditioned on, only $X_{it}$ appears in the response probability at time t. This controls for any influence of lagged dependent variables in $X_{it}$, as well as certain kinds of explanatory variables whose imminent actions is contingent on current and past outcomes on y. This is a strict exogeneity condition.

Another assumption of the model is that the outcomes: $y_{i1}$; . . . ; $y_{iT}$ are independent conditional on $(X_i, u_i)$.

Addionally, The traditional random effects probit model adds the assumption:

$$u_i|X_i \sim \text{Normal } (0, \sigma_u^2) \tag{5}$$

This assumption entails that $u_i$ and $X_i$ are independent and that $u_i$ has a normal distribution. These assumptions are strong and may not be attainable given the nature of the data used in this estimation. According to Wooldridge (2002; 2010) these assumptions can be relaxed by observing:

$$P(y_{it} = 1|\boldsymbol{X_i}) = P(y_{it} = 1|\boldsymbol{X_{it}}) = \Phi(\boldsymbol{X_{it}\beta}), \tag{6}$$

where $\boldsymbol{\beta}_u = \boldsymbol{\beta}/(1 + \sigma_u^2)$

Thus, it is possible to estimate $\boldsymbol{\beta}_u$ from pooled probit of $y_{it}$ on $\mathbf{X}_{it}$, $t = 1,...,T, \quad i = 1,....N$ . This involves direct estimation of the average partial effects. If $u_i$ is truly present, $\{y_{it} : t = 1,....T\}$ will not be independent conditional on $X_i$, with robust standard errors to deal with the requirement of robust inference to account for serial dependence (see Woodridge, 2002: 486).

Woodridge (2002) citing Ruud (1986) discusses how to consistently estimate the slope parameters with some restrictions imposed on the distribution of $X_i$ , mainly that at least one element of $X_i$ with non-zero coefficient is continuous. Since we are only interested in estimating the directions and relative sizes of the partial effects, and not the response probabilities, it is possible to consistently estimate $\boldsymbol{\beta}$ up to scale under very weak assumptions using semi-parametric estimators.

**4. Results and Discussion**

By decomposing the Gini coefficient (equation 1) and the coefficient of variation ( equation 2), it is possible to measure the contribution of a particular source income to overall income inequality as demonstrated by a number of studies (Adams, 1994; Escobal, 2001; Zhu & Luo, 2005).

**Table 2** presents the share of each income component to total income, the Gini coefficient by components of income, the contribution of each component to the overall Gini coefficient, and the contribution to overall inequality in percentage change.

**Table 2: Inequality decomposition by income source for all rural households, 2004-2009**

| Income source | $S_k$ | $G_k$ | $R_k$ | Share | % Change |
|---|---|---|---|---|---|
| non-farm | 0.124 | 0.873 | 0.625 | 0.122 | -0.002 |
| off-farm | 0.021 | 0.923 | 0.289 | 0.01 | -0.011 |
| farm | 0.85 | 0.589 | 0.964 | 0.868 | 0.018 |
| public transfers | 0.003 | 0.967 | -0.255 | -0.001 | -0.004 |
| others | 0.002 | 0.991 | 0.384 | 0.001 | -0.001 |
| Total income | 1.000 | 0.556 | | | |

Source: Computed from ERHS

*Notes:*

$S_k$=Share in total income
Gini coefficient for income source ($G_k$
Gini-correlation with total income ($R_k$)
Share = (Rk*Gk*Sk)/G
% change= (Rk*Gk*Sk)/G-Sk = Contribution of the income source to overall inequality

The results from **Table 2** show that farm income contributes the largest share of income for households, accounting 85% of their income. This income source is followed by non-farm income contributing 12.4%. Throughout the period from 1994–2009, non-farm income has an inequality reducing effect in which a 1% change in non-farm income is likely to reduce inequality by 0.2%. Although, this impact of non-farm income on inequality is very low in magnitude, it is still suggestive of the positive role of non-farm income on equitable income distribution rural Ethiopia. This positive effect of non-farm income remained constant in all years except for 1997, which has inequality increasing effect (see **Table A** annexed).

**Table 3** presents five income sources with non-farm income further decomposed into two of its components –non-farm wage employment and non-farm self-employment income. The results show that non-farm self-employment has a tendency to increase income inequality while non-farm wage employment has the opposite effect on inequality. This result may reflect the separation of the RNFE in which the rich engage in self-employment (own-business) while the poor are more likely to participate in wage-employment as the activities in the self-employment requires higher initial capital, which acts as an entry-barrier for the poor. This result is consistent with what has been found so far by a number of studies in Africa such as by Adams (1994) for Egypt; Canagarajah, et al.( 2001) for Ghana and Uganda; Kijima et al. (2006) for Uganda; and recently Senadza (2012) for Ghana.

Finally, it is important to note that the results from the Gini-decomposition may reflect some limitations of the data set employed. Accordingly, the number of households who participated in 2004 in non-farm wage labour was only 66, which may not provide enough information to decompose income inequality between self-employment and wage-employment categories of non-farm income for the year 2004.

**Table 3: Inequality decomposition by income source for all rural households, 1994-2009**

| **Income source** | **Sk** | **Gk** | **Rk** | **Share** | **% Change** |
|---|---|---|---|---|---|
| non-farm self-employment | 0.074 | 0.935 | 0.654 | 0.081 | 0.007 |
| non-farm wage | 0.036 | 0.953 | 0.515 | 0.031 | -0.004 |
| off-farm | 0.022 | 0.923 | 0.283 | 0.01 | -0.012 |
| farm | 0.864 | 0.589 | 0.968 | 0.878 | 0.014 |
| public transfers | 0.003 | 0.967 | -0.252 | -0.001 | -0.004 |
| Others | 0.002 | 0.991 | 0.376 | 0.001 | -0.001 |
| Total income & Gini | 1.000 | 0.561 | | | |

Source: Computed from ERHS

The results of the probit estimations show that non-farm income has a negative and significant relationship with the probability of being poor (**Table 4**). These results suggest that non-farm diversification can play a positive role in poverty reduction and confirms the findings in other studies from Ghana and Uganda (Canagarajah, et al., 2001), Nigeria (Akaakohol & Aye, 2014) and Ethiopia ( Van Den Berg & Kumbi, 2006; Sosina et al.,2012). This negative association between non-farm income and the likelihood of being poor however does not necessarily imply that poverty reduction can be attributable to the growth of participation in the non-farm sector (see Lanjouw, 2007). Moreover, the poor are mostly limited to the low-return end of the rural non-farm sector in their participation, which means that any growth and expansion in the non-farm sector may not benefit the poor right away. However, as evidenced in India, non-farm earnings can still "contribute to poverty reduction even in cases in which the poor are not directly employed in the Rural Nonfarm Economy" (Lanjouw, 2007:79). This is mostly because earnings from non-farm activities act as a safety-net and play critical role in protecting the poor from further declines in income.[43]

[43] Although the main interest in this analysis lies in identifying the conditional effects, which does not require strictly following the exogenity criterion, some income and asset related variables were excluded in the models. The robustness of the estimated models are checked by including these variables in a different set of estimations. The results show that most other covariates in the probit models are significant and have the expected signs. Accordingly, the probability of being poor declines with education, higher crop income, livestock holding and with access to credit while poor land quality and larger household size increases the household's likelihood of being poor. Estimation that included climate shocks index (a composite index that includes drought, flood and frost experiences by households) for the years 2004 and 2009, shows that the likelihood of poverty also increases statistically significant at less than 1%.

**Table 4: Impact of non-farm income on Poverty headcount (likelihood of being poor)**

| Dependent variable=poor (=1) | Probit RE marginal effects at means | Probit Population averaged |
|---|---|---|
| Ln non-farm income | -0.118*** | -0.104*** |
| | (0.0246) | (0.0220) |
| Age of household head | 0.00412 | 0.00371 |
| | (0.00231) | (0.00211) |
| Male household head(=1) | 0.00935 | 0.00675 |
| | (0.0786) | (0.0718) |
| Highest grade completed | -0.0212 | -0.0191 |
| | (0.0114) | (0.0109) |
| Dependency ratio | 0.622*** | 0.565*** |
| | (0.161) | (0.149) |
| Access to credit dummy | -0.0394 | -0.0325 |
| | (0.0692) | (0.0634) |
| Death of a working member | -0.0322 | -0.0295 |
| | (0.0760) | (0.0690) |
| Tigray region dummy | 0.785*** | 0.700*** |
| | (0.131) | (0.111) |
| Amhara region dummy | -0.251* | -0.226* |
| | (0.102) | (0.0944) |
| South region dummy | 0.822*** | 0.734*** |
| | (0.102) | (0.0916) |
| Access to electricity (=1) | 0.00235 | -0.00508 |
| | (0.0860) | (0.0751) |
| _cons | 0.364 | 0.323 |
| | (0.250) | (0.221) |
| lnsig2u | | |
| _cons | -1.422*** | |
| | (0.293) | |
| No. observations | 2158 | 2158 |
| No. groups | 1022 | 1022 |
| Log likelihood | -1284.9 | |
| chi2 | 280.5 | 346.84 |
| Prob > chi2 | 0.000 | 0.000 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:*

Conditional marginal effects coefficients are estimated for year-intercepts of 1997, 2004 and 2009 and all have negative and significant coefficients when compared to the reference year 1994.

Standard errors adjusted for clustering at household level for the GEE population-averaged model

## 5. Conclusion

This paper examined the effects of non-farm diversification on income inequality and poverty in rural Ethiopia. The results from Gini- decomposition, fixed and random effects models, and probit estimation, show that non-farm diversification largely has a favourable effect on income distribution and poverty. These positive contributions confirm and lend support to the widely held view that the non-farm sector can offer a viable option to reduce rural poverty in countries like Ethiopia where agricultural growth is weak and too often stalled by climatic hazards such as drought.

## References


Abdul-Hakim, R., & Che-Mat, S. H. (2011). Determinants of Farmer's Participation in Off-Farm Employment: A Case Study in Kedah Darul Aman, Malaysia. *Asian Journal of Agriculture and Rural Development*, *1*(2), 27–37.

Adams, R. H. (1994). Non-farm income and inequality in rural Pakistan: A decomposition analysis. *Journal of Development Studies*, *31*(1), 110–133. doi:10.1080/00220389408422350

Adams, R. H. (1999). *Nonfarm income, inequality, and land in rural Egypt* (Vol. 2178). World Bank Publications.

Akaakohol, M. A., & Aye, G. C. (2014). Diversification and farm household welfare in Makurdi, Benue State, Nigeria. *Development Studies Research*, *1*(1), 168–175. doi:10.1080/21665095.2014.919232

Ashley, C., & Maxwell, S. (2001). Rethinking rural development. *Development Policy Review*, *19*(4), 395–425.

Anderson, E., & Deshingkar, P. (2005). Livelihood diversification in rural Andhra Pradesh, India. In Ellis, F., & Freeman, H. A. (Eds.) *Rural Livelihoods and Poverty Reduction Policies* (pp. 55–75). London and New York: Rutledge.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331.

Berdegué, J. A., Ramírez, E., Reardon, T., & Escobar, G. (2001). Rural Nonfarm Employment and Incomes in Chile. *World Development*, *29*(3), 411–425. doi:10.1016/S0305-750X(00)00102-9

Block, S., & Webb, P. (2001). The dynamics of livelihood diversification in post-famine Ethiopia. *Food Policy*, *26*(4), 333–350. doi:10.1016/S0306-9192(01)00015-X

Byerlee, D., De Janvry, A., & Sadoulet, E. (2009). Agriculture for development: Toward a new paradigm. *Annual. Review of Resource Economics*, *1*(1), 15–31.

Canagarajah, S., Newman, C., & Bhattamishra, R. (2001). Non-farm income, gender, and inequality: evidence from rural Ghana and Uganda. *Food Policy, 26*(4), 405–420.

Collier, P. (2008). The Politics of Hunger How Illusion and Greed Fan the Food Crisis. *Foreign Affairs, 87*(6), 67–79.

Deininger, K., & Olinto, P. (2001). Rural Nonfarm Employment and Income Diversification in Colombia. *World Development, 29*(3), 455–465.

De Janvry, A., Sadoulet, E., & Zhu, N. (2005). The role of non-farm incomes in reducing rural poverty and inequality in China. *Department of Agricultural & Resource Economics, UCB.*

Dercon, S., Hoddinott, J., & Woldehanna, T. (2012). Growth and Chronic Poverty: Evidence from Rural Communities in Ethiopia. *Journal of Development Studies*, *48*(2), 238–253. doi:10.1080/00220388.2011.625410

De Waal, A., Seyoum Taffesse, A., & Carruth, L. (2006). Child Survival during the 2002–2003 Drought in Ethiopia. *Global Public Health*, *1*(2), 125–132.

Ellis, F. (2005). Small farms, livelihood diversification, and rural-urban transitions: Strategic issues in Sub-Saharan Africa. *The Future of Small Farms*, 135.

Ellis, F. (2007). Strategic Dimensions of Rural Poverty Reduction in Sub-Saharan Africa. Presented at the Rural Development Retrospect and Prospect: A Workshop for Judith Heyer.

Escobal, J. (2001). The Determinants of Nonfarm Income Diversification in Rural Peru. *World Development*, *29*(3), 497–508. doi:10.1016/S0305-750X(00)00104-2

Feldman, A. L. (2009). Decomposition of the Gini coefficient using Stata. Presented at the Mexican Stata Users’ Group Meetings 2009, Stata Users Group.

Ferreira, F. ., & Lanjouw, P. (2001). Rural Non-farm Activities and Poverty in the Brazilian Northeast. *World Development*, *29*(3), 509–528.

Gollin, D., Parente, S., & Rogerson, R. (2002). The role of agriculture in development. *American Economic Review*, 160–164.

Himanshu, Lanjouw, P., Murgai, R., & Stern, N. (2013). *Non-Farm Diversification, Poverty, Economic Mobility and Income Inequality : A Case Study in Village India*. Washington, DC: World Bank. Retrieved from https://openknowledge.worldbank.org/handle/10986/15555

Jonasson, E., & Helfand, S. (2008). *Locational Determinants of Rural Non-agricultural Employment: Evidence From Brazil* (Working Paper No. 200802). University of California at Riverside.

Kijima, Y., Matsumoto, T., & Yamano, T. (2006). Nonfarm employment, agricultural shocks, and poverty dynamics: evidence from rural Uganda. *Agricultural Economics*, *35*, 459–467. doi:10.1111/j.1574-0862.2006.00191.x

Lanjouw, P. (2007). Does the rural nonfarm economy contribute to poverty reduction? *Transforming the Rural Nonfarm Economy: Opportunities and Threats in the Developing World*, 55–79.

Lazarte-Alcala, N., Adkins, L., Lahiri, B., & Savvides, A. (2012). *Remittances and Income Diversification in Bolivia's Rural Sector* (pp. 1–34).

Lerman, R. I., & Yitzhaki, S. (1985). Income inequality effects by income source: a new approach and applications to the United States. *The Review of Economics and Statistics*, 151–156.

Nega, F., Marysse, S., Tollens, E., & Mathijs, E. (2009). Diversification, Income Inequality and Social Capital in Northern Ethiopia.

Olugbire, O., Falusi, A., Adeoti, A., Oyekale, A., & Adeniran, O. (2011). Non-Farm Income Diversification and Poverty Reduction in Nigeria: A Propensity-Score Matching Analysis. *Continental Journal of Agricultural Science*, *5*(3).

Reardon, T., Taylor, J. E., Stamoulis, K., Lanjouw, P., & Balisacan, A. (2000). Effects of non-farm employment on rural income inequality in developing countries: an investment perspective. *Journal of Agricultural Economics*, *51*(2), 266–288.

Reardon, T., Berdegue, J., & Escobar, G. (2001). Rural Nonfarm Employment and Incomes in Latin America: Overview and Policy Implications. *World Development*, *29*(3), 395–409.

Ruben, R., & Van den berg, M. (2001). Nonfarm Employment and Poverty Alleviation of Rural Farm Households in Honduras. *World Development*, *29*(3), 549–560. doi:10.1016/S0305-750X(00)00107-8

Scharf, M. M., & Rahut, D. B. (2014). Nonfarm Employment and Rural Welfare: Evidence from the Himalayas. *American Journal of Agricultural Economics*, *96*(4), 1183–1197. doi:10.1093/ajae/aau040

Sosina, B., & Barrett, C. (2012). Employment Dynamics in the Rural Nonfarm Sector in Ethiopia: Do the Poor Have Time on Their Side? *Journal of Development Studies*, *48*(9), 1223–1240. doi:10.1080/00220388.2012.671476

Sosina, B., Barrett, C. B., & Holden, S. T. (2012). Does the Nonfarm Economy Offer Pathways for Upward Mobility? Evidence from a Panel Data Study in Ethiopia. *World Development*, *40*(8), 1634–1646.

Tubiana, P. J., Rajendra K. Pachauri, Laurence. (2012). *Towards Agricultural Change?*. TERI Press.

Uregia, N. T., Desta, M. D., & Rashid, S. (2012). *Welfare Impacts of Rising Food Prices in Rural Ethiopia: a Quadratic Almost Ideal Demand System Approach* (2012 Conference, August 18-24, 2012, Foz do Iguacu, Brazil No. 124861). International

Association of Agricultural Economists. Retrieved from http://ideas.repec.org/p/ags/iaae12/124861.html

Van Den Berg, M., & Kumbi, G. E. (2006). Poverty and the rural nonfarm economy in Oromia, Ethiopia. *Agricultural Economics*, *35*, 469–475. doi:10.1111/j.1574-0862.2006.00192.x

Van De Walle, D., & Cratty, D. (2004). Is the emerging non-farm market economy the route out of poverty in Vietnam? *Economics of Transition*, *12*(2), 237–274. doi:10.1111/j.0967-0750.2004.00178.x

Webb, P., & Reardon, T. (1992). Drought impact and household response in East and West Africa. *Quarterly Journal of International Agriculture*, *31*, 230–230.

Woldenhanna, T., & Oskam, A. (2001). Income diversification and entry barriers: evidence from the Tigray region of northern Ethiopia. *Food Policy*, *26*(4), 351–365. doi:10.1016/S0306-9192(01)00009-4

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, Massachusetts: MIT press.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, Massachusetts: MIT press.

World Bank. (2007). *World Development Report 2008: Agriculture for Development*. Washington, DC: The World Bank.

Zhu, N., & Luo, X. (2005). Nonfarm activity and rural income inequality: A case study of two provinces in China. *World Bank Policy Research Working Paper*, (3811).

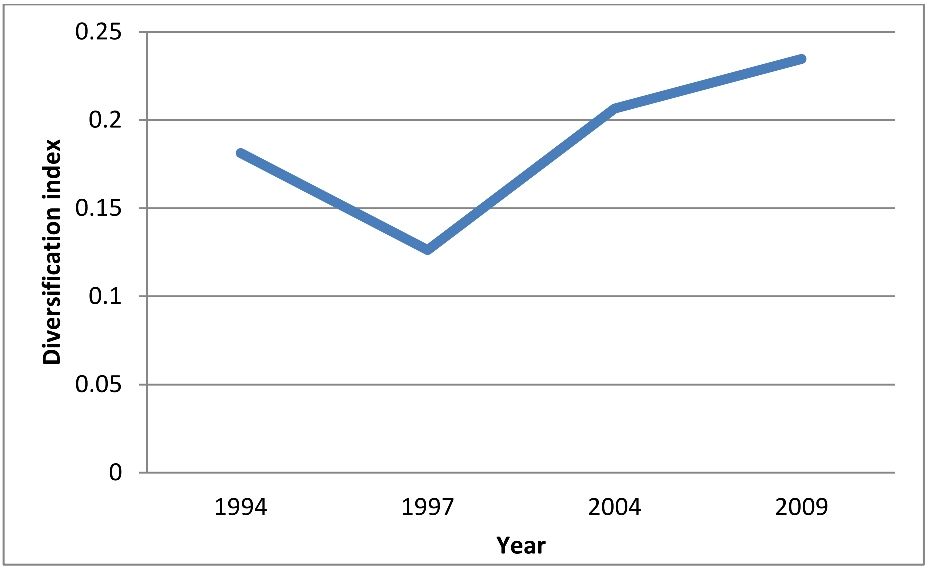
**Annex**

**Table A: Contribution to income inequality by income source for all rural households, 2004-2009**

| | Year | | | |
|---|---|---|---|---|
| | **1994** | **1997** | **2004** | **2009** |
| **Source** | **% Change** | **% Change** | **% Change** | **% Change** |
| non-farm | -0.014 | 0.03 | -0.006 | -0.02 |
| off-farm | -0.014 | -0.008 | -0.01 | -0.007 |
| farm | 0.041 | -0.021 | 0.02 | 0.03 |
| public transfers | -0.013 | -0.001 | -0.003 | -0.002 |
| others | 0 | 0 | -0.001 | -0.001 |
| Total income Gini | 0.58 | 0.59 | 0.496 | 0.528 |

Source: computed from ERHS

**Figure 1: Income diversification using the Herfindal index, for all activities 1994–2009**




Source: computed from ERHS 2004–2009

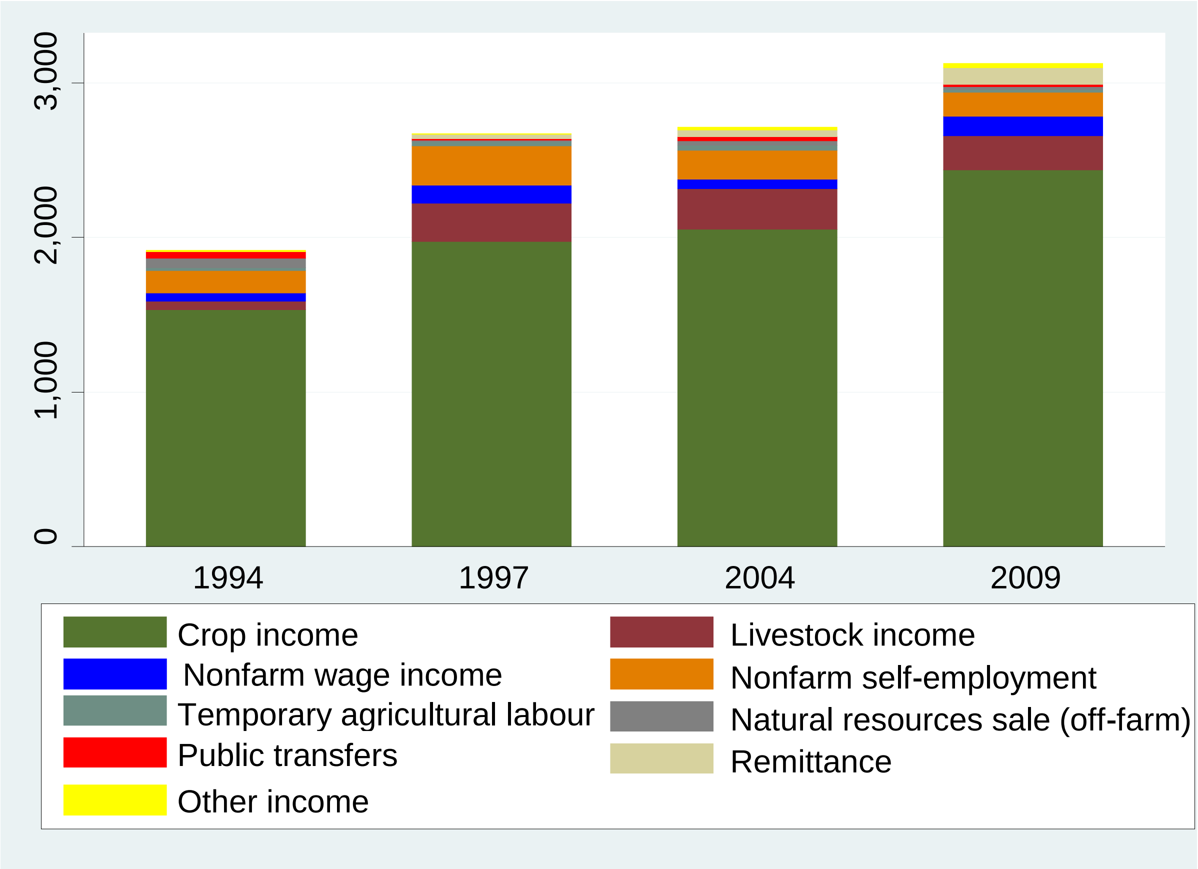
*Notes:*

The diversification index (DI) is calculated as the inverse Herfindahl index as:

$$DI_i = \left[ \frac{1}{\sum a_j^2} \right]_i$$

where each $a_j$ represents the proportional contribution of each livelihood activity $j$ to household $i$'s overall income. If total income is distributed equally among the different sources, the maximum possible value of the index will be close to 1 and the minimum possible value is 0, which refers to the situation when all income is earned from a single source (Anderson & Deshingkar, 2005).

**Figure 2: Mean Income Composition from Various Sources 1994–2009**




**Notes**:
Income is expressed in mean annual terms based on 1994 prices.
Crop income includes the monetary value of all crops produced in Meher and Belg seasons
Livestock income includes income earned from the sale of live animals (not because of distress sale that has adverse effect on asset holding) and income from animal products such as milk, cottage cheese, meat, hides and skins etc. The 1994 round does not include income from the sale of animal products as it was not reported in the data.
Nonfarm wage income is composed of income earned from the following sources as reported in the data: Professional (Teacher, government worker), skilled labourer (Builder, Thatcher), Soldier, driver/Mechanic, unskilled non-farm worker, domestic servant, and guard.
Nonfarm self-employment largely constitutes income earned from own-business activities such as Weaving/spinning, milling, handicraft, including pottery, trade in grain/general trade, income from services such as traditional healer/religious teacher, transport (by pack animal), selling injera and wett (food),barbary and tailoring. It also includes the making and selling of local drinks, carrying goads (porter), builder (masonry), making roof for houses, rock splitting, and fruit and vegetable vending.
Income from the sale of Natural resources is aggregated from the making and selling charcoal and Collecting and selling firewood or dung-cake.

Temporary agricultural labour includes income earned from engaging in someone's farm in return for in-kind income (in terms of sharecropping) or in daily wage. In order to control for locational effect, only activities reported within the village were used.

## Essay 4

# Does Social Protection favour Diversification as Autonomous Climate Change adaptation Strategy? Evidence from Rural Ethiopia*


**Abstract**

It is widely predicted that climate change will have an adverse impact on Ethiopian agriculture and exacerbate the problem of food insecurity. In this context, social protection schemes can potentially contribute to households' autonomous adaptation by reducing vulnerability to climatic shocks. This paper examines the impacts of the Productive Safety Net Programme (PSNP), as the main the social protection scheme, on autonomous adaptation strategies by taking the case of household income diversification into non-farm activities. It uses non-experimental approaches namely; Difference-in-Differences combined with Propensity Score Matching for a panel of 1,306 rural households from the two recent rounds of the Ethiopian Rural Household surveys (ERHS) for the years 2004 and 2009. Taking advantage of the extensive data available on a range of activities and incomes, the paper makes a conceptual distinction between non-farm and off-farm income, and uses the recent Adaptive Social Protection framework to examine the impact of the PSNP. The results indicate that receiving transfers from the PSNP, on average increases income from non-farm activities. This partly confirms the hypothesis that social protection can promote positive adaptation strategies and serve as an effective means of reducing the vulnerability of smallholders to climate change induced shocks. However, an increase in the off-farm income components may be taken as having a negative impact climate change adaptation.



Keywords: Climate Change Adaptation, Social Protection, Diversification, Difference-in-Differences, Ethiopia

JEL: D12, O13, Q12, Q54, R20


*The first three sections of this paper draws on previously published article by Weldegebriel and Prowse titled 'Climate-Change Adaptation in Ethiopia: To what Extent Does Social Protection Influence Livelihood Diversification?' in Development Policy Review, 2013, 31(S2).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## 1. Introduction

Social Protection (SP) is increasingly viewed as an important part of development agenda due to growing experience and increasing evidence that it can effectively contribute to poverty reduction (Davies et al., 2009; Wood, 2011; Bene et al., 2012; Davies et al., 2013; Fiszbein, Kanbur, & Yemtsov, 2014). Many SP policy instruments have targeted and contributed to the efforts of reducing the vulnerability associated with variations and extremes in climate and their impact on rural livelihoods. As a result, there is a growing recognition of the role of social protection programmes in addressing climate-related shocks and vulnerabilities (Davies et al., 2008; World Bank, 2010; Bene et al., 2012; Macours, Premand, & Vakis, 2012; Davies et al., 2013).

However, little empirical evidence exists about the extent and conditions by which SP schemes are able to contribute to autonomous climate change adaptation at the household level. This type of adaptation is particularly critical in poor countries like Ethiopia as they cannot afford the high cost of planned adaptation measures that require huge investments in infrastructure and technologies (Swart & Raes, 2007).Thus, given the magnitude of the projected impacts of climate change on Ethiopia (Haakansson, 2009; Conway & Schipper, 2011), there is a need to evaluate to what extent the existing social protection scheme i.e. the Productive Safety Net Programme (PSNP) contributes to autonomous climate change adaptation.

The projected impacts of climate change also pose important questions for the implementation of SP schemes (Davies et al., 2009; Conway & Schipper, 2011). For example, it remains unclear to what extent such schemes influence households' diversification strategies and help them manage climate-related risks. As shown by many studies, a major aspect of risk managing strategy among smallholders is diversification, which helps households build resilience in the face of various shocks (Ellis, 2000; Barrett, Reardon, & Webb, 2001a; Haggblade, Hazell, & Reardon, 2010; Macours et al., 2012 ; Zorom et al,  2013). While it has long been recognized that diversification is an important strategy for adapting to climate change at household level (see Prowse & Scott, 2008; Sabates-Wheeler et al., 2008; Campos,Velázquez, & McCall, 2014), there is little empirical evidence on interventions that may help promote such strategies in the context of adapting to climate change.

This paper bridges this gap in the literature by investigating the role of SP in climate change adaptation in Ethiopia and by providing empirical evidence on the possible links between participation in the program and diversification by smallholders, which is considered as a major autonomous adaption to climate change in Africa ( see Below et al., 2010).

The PSNP as the main social protection programme in Ethiopia was launched in 2005 as part of the Food Security Programme designed to proactively address the persistent problem of food insecurity by breaking the cycle of dependency on emergency food relief. It is the largest social protection programme in Africa with 7.2 million beneficiaries (Gilligan, Hoddinott, & Taffesse, 2009).[44] Some micro impact evaluation studies have been conducted on the effect on the program on food security and growth in livestock holdings (Devereux et al., 2006; Devereux et al., 2008; Gilligan et al., 2009; Berhane et al., 2011), on livestock and tree holding (Anderson et al., 2009), on schooling and child labour (Hoddinott, Gilligan, & Taffesse, 2009), and more recently on technology adoption (Alem & Broussard, 2013).

[44] The PSNP is planning to reach approximately 8.3 million beneficiaries in 1.5 million households between 2010 and 2014. The programme aims to graduate the majority of its current beneficiaries in the four regions and expand its operations to pastoral regions of Afar and Somali which were not part of the programme in the first phase (FDRE, 2010).

However, no impact evaluations on the effect of the PSNP on climate change adaptation outcomes are conducted except for our previous study (see, Weldegebriel & Prowse, 2013) that used cross-sectional data from a 2008 survey.[45] However, the data did not have information on income from labour migration and remittances and some core variables pertaining to the programme targeting criteria could not be included in the estimations. This has limited our ability to establish robust causal claims about non-farm diversification. Despite this limitation however, the article identified useful indicators on how social protection influences smallholders' autonomous adaptation strategies. This paper complements and extends our previous analysis using a panel data and a combination of different evaluation approaches.[46]

The paper is structured as follows: Section 2 discusses the relevance of diversification as an autonomous adaptation strategy to climate change and gives a brief review of the literature on diversification in Ethiopia. Section 3 describes conceptual links between social protection and climate adaptation. Section 4 presents the methodology used in estimating the programme's impact. In section 5, the results of the mean treatment effects are discussed and section 6 gives concluding remarks.

## 2. Climate Change Adaptation and Livelihood Diversification

The IPCC's Fourth Assessment Report indicates that the majority of countries in sub-Saharan Africa are likely to experience an increase in mean temperatures and greater variability in rainfall patterns higher than other regions in this century (IPCC, 2007). Likewise, the IPCC's

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[45] The data used in the article come from a household survey carried out in 2008 in four regions of Ethiopia that are served by the PSNP. The survey was collected for a "Trends in PSNP Transfers within Targeted Households" study by Devereux et al. (2008).

[46] Panel data is better suited for policy evaluations since it can solve the endogeneity problem that leads to erroneous conclusions in policy evaluation.

Special Report on Extreme Weather Events (SREX) indicates the region is ‘extremely vulnerable to climate extremes’ such as droughts, heat waves and floods (IPCC, 2012: 253). The report specifies a likely increase in heavy precipitation in East Africa which could possibly cause more floods. There is less confidence in drought projections due to inconsistent results in predictions of drought changes over the region.

The impact of climate change on Ethiopia can be explained in terms of how temperature (which has been increasing gradually in recent decades) and precipitation (which has shown some signs of greater variability) are likely to unfold in coming decades (Conway and Schipper, 2011).

National projections indicate that mean annual temperature is likely to increase significantly when compared to the 1961-1990 level, by a maximum of 1.1$^{0}$C by 2030, 2.1 $^{0}$C by 2050 and 3.4$^{0}$C by 2080 (FDRE, 2007).[47] Famine Early Warning Systems Network (FEWS NET) (2012b) also projects most of Ethiopia will experience an increase in temperature greater than 1.0°C by 2039 if recent warming trends continue (with the south-central part of the country likely to warm most).

Regarding rainfall, the IPCC’s projections indicate an aggregate of 7% increase for East Africa in the last decade of this century compared to the same period in the previous century. However, national figures show that the average countrywide annual rainfall pattern remained constant between 1951 and 2006 and projections suggest little change in the future (FDRE, 2007).[48] However, recent reports based on three decades of *Belg* and *Kiremet* rainfall

[47] Conway and Schipper (2011) concur with multi-model averages of 1.2$^{0}$C in the 2020s, 2.2$^{0}$C in the 2050s and 3.6$^{0}$C in the 2080s.
[48] There is a lot of uncertainty with regards to how rainfall patterns unfold following climate change in Ethiopia. This is due to the lack of robust climate model simulations that arises from the complex interaction of various

observations, highlight a 15–20 per cent decrease across southern, south-western and south-eastern areas. This observed decline in rainfall overlaps with densely-populated locations (FEWS NET, 2012b).[49]

### 2.1. Autonomous Adaptation to Climate Change

Many writers now argue that adaptation measures are the most viable response to climate change in poor countries (Pielke et al., 2007; Ayers & Forsyth, 2009). Current efforts at mitigation are more or less bounded by reaching international agreements on issues that are proving difficult to negotiate. In contrast, adaptation strategies are more tangible and applicable as they consist of measures that try to lessen the impacts of climate change on economies, people and their livelihoods (Leavy & Greeley, 2011).

Thus, adaptation measures in poor countries are a vital response to climate change. There are two types of adaptation responses (1) autonomous adaptation referring to actions taken by individuals in the face of changing climatic conditions, such as a shift in rainfall and (2) planned and mostly national-level measures that invest in technology and infrastructure across sectors (Prowse and Scott, 2008; Pelling, 2010). Autonomous adaptation involves *ex ante* risk management, which in the livelihoods literature is distinguished from *ex post* coping strategies. Ellis (2000:45) asserts that *ex ante* risk management refers to "the way households respond over the long term to adverse events, cycles and trends" while coping strategies involve spontaneous and often desperate reactions to unforeseen circumstances. Similarly, Scoones (1998:6) asserts *ex ante* risk management reflects "long-term shifts in livelihood

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phenomena like sea surface temperature, moisture sources and atmospheric particulates (Conway and Schipper, 2011).

[49] Based on the assumption that observed trends in rainfall continue, it is projected *Belg* and *Kiremet* rains will decline up to 150 mm in the most densely populated areas of western and southern Ethiopia, and across the south-central and eastern parts (affecting pastoralists and agro-pastoralists).

strategies while coping is temporary adjustments in the face of change" (*ibid*). Ellis (1998:13) states risk management involves a premeditated decision to diversify income sources to avoid harm to household wellbeing in the event of income failure in one activity, whilst coping is "ex-post consumption management in the wake of crisis". This distinction between risk management and coping strategies is important as it frames our discussion of livelihood diversification as an adaptation strategy.

## 2.2 Livelihood diversification

Livelihood diversification is often defined as a process by which rural households construct a more diverse range of activities to survive and improve their standard of living. It involves the maintenance of a range of activities and occupations. Diversification also refers to the balance between different sources (Ellis, 2000). According to Barrett et al.(2001), diversification is mostly measured by using income earned from different activities/sources. Income allows a clear interpretation of results as it comprises both cash and in-kind contributions to household welfare.

Inter-household differences exist in the entitlements and access to alternative activities (Ellis, 2000) and often a distinction is made between natural-resource based activities and non-natural-resource-based activities.[50]Following Ellis (1998, 2000) this paper disaggregates total household income into categories and sub-categories which reflect the different features of

[50] Natural-resource based activities include collection or gathering, food cultivation, non-food cultivation (e.g. export crops), livestock keeping, and pastoralism. It also includes off-farm activities that depend on natural resources (Sharp, Devereux, & Amare, 2003; Degefa, 2005). Non natural-resource based activities or income sources include rural trade (marketing of inputs and outputs), other rural services (e.g. vehicle repair), rural manufacturing, remittances (urban and international), and other transfers such as pensions deriving from past formal employment.

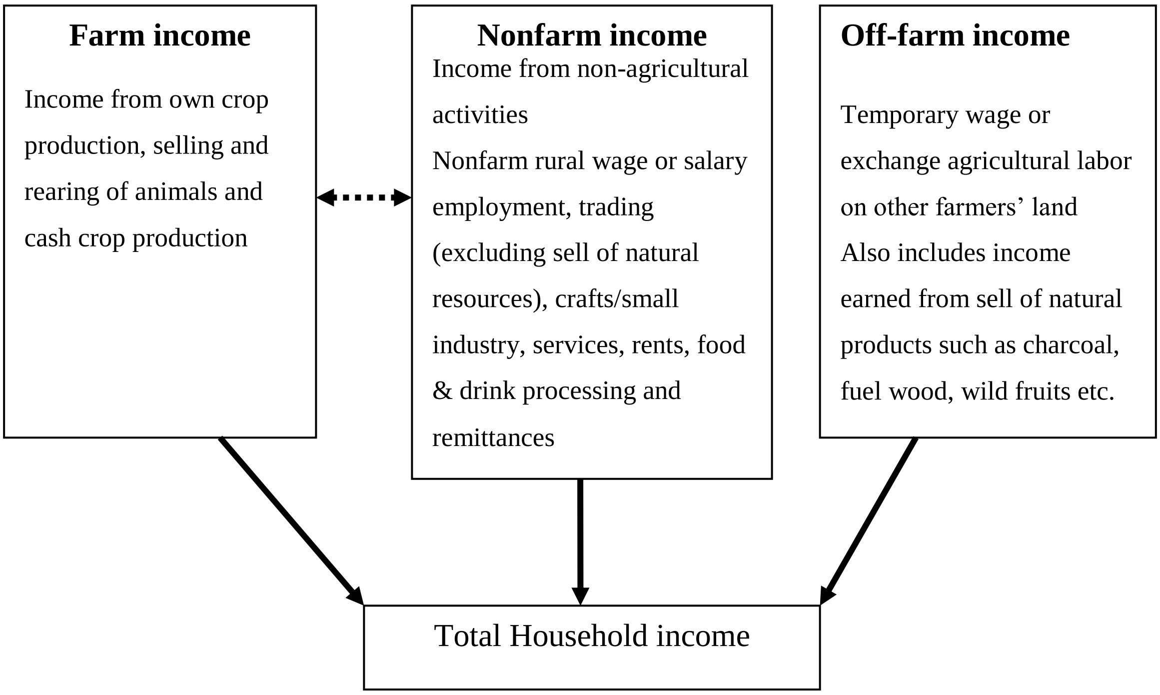
the resources required to generate them, their seasonality, accessibility and location and defines them as follows (see also **Figure 1**):

*Farm Income:* Income generated from one's own farming, whether on owner-occupied land or leased land. Farm income broadly defined includes livestock as well as crop income and comprises both consumption of own farm output as well as the cash income obtained from output sold.

*Off-farm Income:* Off-farm income refers to temporary "wage or exchange labour on other farms within agriculture" (Ellis, 1998:5). This, in most instances, involves working on others farms for wages or other arrangements such as sharecropping or the exchange of labour in kind. Off-farm income is strictly defined as income generated from working outside of one's own farm through participating in agricultural activities such as ploughing, weeding or harvesting on another farmer's land. Moreover, as discussed by Ellis (2000), we also consider income from local environmental resource extraction such as firewood collection, charcoal production and gathering of wild fruits as off-farm income.

*Non-farm Income:* Non-farm income refers to non-agricultural income sources, either in secondary and tertiary sectors (Barrett et al. 2001). Non-farm income also includes salaries or remittances from formal employment in market-based activities (Ellis, 1998). This paper uses Ellis's (2000) classification to account for typical non-farm activities that are pursued by rural households in Ethiopia: non-farm rural salaried employment; non-farm rural self-employment (sometimes called business income); rental income obtained from leasing land or property; urban to rural remittances arising from within national boundaries; other urban transfers to rural households (e.g. pension payments and international remittances arising from cross-border migration).[51]

**Figure 1: Classification of Income by Livelihood Activities**




Source: Ellis (2000)

## 2.3. Diversification and Adaptation

Diversification can have both positive and negative impacts. The impacts are positive if livelihoods are more secure and if the adverse impacts of seasonality are reduced, for example, through consumption smoothing, risk reduction, complete use of available

[51] Migration is recognized as one of the most important form of diversifying income for rural livelihoods (Ezra and Kiros, 2001). However, there seems to be a lack of consistency in the terms used to classify migration in the literature. For instance, some writers consider migration as a diversification strategy in its own right separate from the categories outlined above (Sabates-Wheeler et al., 2008), while others directly or indirectly treat it as part of nonfarm activities (Ellis, 1998; Reardon, 1997). For analytical purposes, this paper leans towards the latter classification and treats migration as part of non-farm activities and includes income from labour migration and remittances in the analysis.

household labour and skills, and cash generation for investment in human or physical capital. However, diversification can increase households' vulnerability if for instance it involves dependence on natural resources that are easily affected by weather shocks (Ellis, 1998). Regarding adaptation, a common argument is that diversifying into non-farm activities is preferable to activities tied to farming (see Sabates-Wheeler et al., 2008). For example, most non-farm activities have different risk profiles than farming (such as trade, or remittances) and can improve food security as they provide income during lean seasons caused by weather variability (World Bank, 2009). A more extreme version of this argument is that "diversification within natural-resource use may be regarded as reinforcing vulnerability to climate change" (Thomas and Twyman, 2005: 118).

The positive role of non-farm activities and income is also suggested by Bryan et al.'s (2009) study on the determinants of adaptation to climate change in Ethiopia and South Africa. Next to basic household and demographic characteristics (mainly education and age), non-farm income is identified as having the most positive effect in encouraging adaptation options in agricultural livelihoods.

Although the significant role of non-farm diversification for rural livelihoods is well-documented, there is very little discussion on it in the adaptation literature (Cannon, 2014). Thus, there are a few studies that demonstrate the role of non-farm diversification in climate change adaptation. Below, we provide a survey of these studies in the African context.

Osbahr et al. (2008) used qualitative data from a case study in Mozambique to explore specific cross-scale local responses to climate shocks. They find that non-farm diversification and collective dual land-use system are the prominent responses to climatic shocks. The main diversification strategy is identified as an economic migration for piece jobs or wage labour to cities in Mozambique and in South Africa.

Hassan and Nhemachena (2008) analysed the determinants of farm-level climate adaptation measures in 11 African countries using a multinomial choice model fitted to data from a cross-sectional survey of over 8000 farm households. They find that farmers adaptation options involve increased diversification, both on-farm and non-farm. Similarly, Paavola (2008) also find that livelihood diversification is the main strategy for living with climate variability and other stresses in Morogoro, Tanzania.

Apata, Samuel, and Adeola (2009) using data from 350 households from south-Western Nigeria and applying logistic regression find that diversification into non-farm activities is the most common adaptation practice.

Tacoli (2009:520) also argue that income diversification and especially circular migration (non-farm) serves as an adaptive response to climate change in the context of rain-fed agriculture. And further suggest that "building on existing patterns and trends, such income diversification will become an increasingly important element of adaptation to slow-onset climate change".

In this paper, we follow the frequent distinction between diversification for necessity and diversification by choice (Hart, 1994, cited in Ellis, 1998), and define the relationship between diversification and climate adaptation in a tripartite manner. We view increased non-farm income as positive adaptation. Second, we view increased farm income as a neutral form of adaptation (as greater income from farming tells us nothing of diversification or commercialisation within farming). For example, greater income from farming can either increase or decrease exposure to climate variability. This view, however, only refers to the income earned from farming and is likely to be limited in terms of identifying positive aspects of farm-level adaptations such as adopting drought resistant crop varieties. Finally, by applying a strict definition of off-farm activities as temporary farm wage or in-kind employment, as well as collection of natural resources, we consider an increase in off-farm income as an indicator of distress and therefore a negative form of adaptation. Such a categorisation is only intended to assess adaptive capacity in the very short term. Evidently, more severe medium- and long-term climatic changes can easily render such a schema obsolete (Betts et al., 2011).

### 2.4. Diversification in Ethiopia

Although agriculture remains the main source of income and employment, rural non-farm income is gaining importance in most rural areas in developing countries. As a result, 35–50% of rural incomes were attributed to the rural non-farm economy in developing countries at the start of the new millennium (Haggblade et al., 2010). A figure frequently cited for Ethiopia ranges between 25-36 % (Degefa, 2005; World Bank, 2009).[52]

The importance of non-farm activities in Ethiopia varies by region (Carswell, 2002) and livelihood zone (LIU, 2011).The most important source of cash income for most rural households comes from crop sales in the cropping livelihood zone (broadly comprising Tigray, Amhara, Beneshangul Gumuz, Gambella, South Region and the western and northern parts of Oromiya) and livestock sales for pastoral and agro-pastoral zones (roughly corresponding to Somali and Afar). Migrant labour is common in the parts of Amhara and Tigray which were the epicentre of famines in the 1970s and 1980s. In these areas, cash income from migrant labour ranges between 31-54% of total household income. Income from non-farm and off-farm activities such as petty-trading and self-employment constitute up to

[52] These figures are likely to include off-farm activities as the literature on diversification lacks a standard way of classifying nonfarm and off-farm activities (see Barrett et al., 2001).

60% of households' income in some part of the country. For instance, petty-trading is significant in densely-populated areas of the SNNPR. The collection of firewood and grass for fodder sales (defined as self-employment by LIU, 2011) is common in the lowlands and pastoral areas. Income from firewood and charcoal sales contributes more than 9% of total cash income in western Tigray, southern Amhara, southern Afar and the southern foothills of Hararge (LIU, 2011).

Studies conducted at regional levels in Ethiopia also confirm the important role of non-farm diversification. Woldenhanna and Oskam (2001) in their study in Tigray in North Ethiopia, show that households diversify into non-farm activities according to their wealth category. Poorer households mostly engage in wage labour whereas wealthier households are able to enter higher return activities. Devereux and Sharp (2006) indicate that poor households in Wollo region engage in multiple non-farm activities in order to maintain their livelihoods. Van Den Berg and Kumbi (2006) found that in the largest region in Ethiopia (Oromia), the poor participate actively in the non-farm economy. A recent study by Porter (2012) reports that non-farm income substitute lost income from crops due to agricultural shocks in Ethiopia. Block and Webb (2001) show that a lack of non-farm income is perceived as a risk factor by 23 % of their sample in their study of household risk perceptions in Ethiopia.

A recent national level study finds that participation in non-farm activities is an essential source of additional household income and can help households to cope better with shocks. It also notes that in food insecure areas, and for the poorest households, non-farm activities could play a crucial role in ensuring livelihoods (World Bank, 2009:56).

In summary, diversification can serve as an important strategy for adapting to climate variability and associated risks serving as the main form of self-insurance (Barrett et al., 2001: 322) in the absence of formal, market-based insurance in most regions in the country (e.g. crop insurance). More importantly, however, diversification does not seem to be a transient phenomenon or one just associated with survival in the face of adversity such as climate related disaster but ‘‘it may be associated with success at achieving livelihood security under improving economic conditions as well as with livelihood distress in deteriorating conditions’’(Ellis, 1998:2).

A report by the World Bank recognizes the need to focus on diversification along with taking macroeconomic measures to lessen the impact of climate risks in Ethiopia. The following quotation vividly encapsulates this point:

> “...accelerated diversification of income and employment sources away from climate-sensitive sectors such as agriculture is likely to become increasingly important under a more erratic climate. It should be explored in closer detail, particularly because it holds promise to be a cost-effective way to eliminate residual welfare damage caused by climate change”(World Bank, 2010: xxvi–xxvii).

### 3. Adaptive Social Protection and the PSNP

In the previous section, we have seen the extent of Ethiopia’s vulnerability to climate change which calls for strengthening the existing autonomous adaptation strategies such as livelihood diversification. In this section, the conceptual and theoretical links between climate change adaptation and social protection are explored to lay the foundations for the subsequent analysis.

Social protection can be defined as an intervention involving a range of activities carried out by public and private entities that aim to reduce the vulnerability of the poor to livelihood risks through the provision of income and other transfers (Devereux & Sabates-Wheeler, 2004). Some of the activities considered as part of social protection programs include old age pensions, food subsidy programs, public works (for food or cash), emergency cash transfers, urban food distribution programs, school feeding programs and input subsidies.

The concept of social protection has long been associated with periods of economic recession and was often considered as a "welfarist" and "unproductive" venture (Farrington et al., 2004:3). Recently, however, international organizations such as the World Bank have begun to view the concept in a more positive light due to the growing evidence that it contributes to development and poverty reduction. Various studies on social protection indicate that it can play a significant role in promoting productive investment in sectors such as smallholder agriculture; increase the resilience of households to shocks that can deplete their productive assets; enhance the risk taking and entrepreneurial abilities of people; and help to smooth consumption (Devereux & Sabates-Wheeler, 2004; Davis et al., 2009).

A recent literature suggests that social protection programmes can be an effective way of supporting adaptation to climatic risks as they can reduce vulnerability to climate-induced shocks (for example, see Linnerooth-Bayer, 2008; Siegel, Gatsinzi, & Kettlewell, 2011; Davis et al., 2013). Indeed, one way in which social protection can contribute to adaptation is through supporting existing strategies pursued by local people to better manage risks. For example, Johnson and Krishnamurthy (2010) indicate that conditional transfers from social protection programmes in Mexico and Nicaragua had significant impacts on household decisions about consumption and investment and encourage household strategies such as economic migration. More broadly, safety-net measures not only provide an effective means of protecting livelihoods against natural hazards but can also help to transform livelihoods (see **Figure A**, annexed).

To understand the channels through which such schemes can support adaptation, it is helpful to present Devereux's (2006:2) explanation of how social protection schemes can address specific types of entitlement failure:

1. *Production-based entitlement failure* – Agricultural risks such as harvest failures or persistent food production deficits can be the sources of production-based entitlement failure. Suitable social protection responses include transfers in the form of fertilizer subsidies and starter packs. Such forms of support increase farm income and enhance production entitlements.
2. *Labour-based entitlement failures* – Limited employment opportunities coupled with a decline in real wages can trigger labour-based entitlement failures. Possible policy responses include public works programmes as well as setting minimum wage legislation.
3. *Trade-based entitlement failure* – Market failure and decline in the terms of trade can cause the failure of exchange entitlements. Here pricing policies, such as food price subsides, as well as resolving market failures, can be considered.
4. *Transfer-based entitlement failure* – The failure of informal safety nets, emergency food aid or absence of social protection can be major sources of vulnerability. Social protection responses include the provision of food aid or cash transfers.

Addressing food insecurity is a major policy challenge in Ethiopia. Since the mid-1980s, the country has relied on emergency interventions to meet national food deficits (FDRE, 2005).[53] However, such interventions were rendered ineffective due to recurrent droughts, resulting in

[53] For instance according to the Famine Early Warning Systems Network (FEWS NET), an estimated 3.7 million people have required emergency food assistance in August 2012. And a similar number of people have accepted relief food in October 2012 (FEWS NET, 2012). A more recent report indicates that despite the decline in the number of people needing food assistance as compared to five year-average, 2.5 million people are still in need of assistance during October 2014 to March 2015(FEWS NET, 2014).

a gradual deterioration of households' food security status (Barrett and Maxwell, 2005). As a response, proactive food security enhancing measures were introduced to try to break the cycle of hunger and food-based emergency assistance (FDRE, 2004). One such measure is the Productive Safety Net Programme (PSNP) initiated by the Government of Ethiopia and a group of donors in 2005.[54] The programme is designed to address the needs of food insecure households through 'multi-year predictable resource transfers' rather than emergency humanitarian aid. It aims to provide transfers to the food insecure population in chronically food-insecure districts in a way that prevents asset depletion at the household level and creates assets at the community level (FDRE, 2004).

The PSNP is currently the largest social protection scheme in sub-Saharan Africa with an estimated 8.3 million participants enrolled in its 2010-2014 phase, roughly accounting for 10% of Ethiopia's population and covering the majority of the 500 districts in the country (Devereux and Guenther, 2009; FDRE, 2010)[55]. It has two components: labour-intensive public works and direct support. Households with able-bodied adults participate in public works to enhance community assets, such as building schools, health posts, and roads before receiving the transfers. From early 2008, the public works programme paid individuals from targeted households 10 Birr per day or food of equivalent value, equivalent to roughly US$1 (FAO/WFP, 2009). Households with little labour (the aged, disabled, chronically ill) are exempted from public works and receive direct transfers either in the form of food or cash (FDRE, 2004).

[54] The joint donor group includes the Canadian International Development Agency (CIDA), the UK Department for International Development (DFID), Development Co-operation Ireland, the European Commission (EC), and the US Agency for International Development (USAID), the World Bank, and World Food Programme (WFP).
[55] According to recent developments, a new phase of the programme named PSNP-4 is due to be launched in 2015 and will stay operational until 2020 (The Ethiopia Observatory, 2014).

The PSNP aims to address three interrelated objectives, which according to Devereux and Guenther (2009:7), can be viewed as a ‘traffic light’ with the red standing for protection against crisis to green for promoting of livelihoods. These objectives are:

1. Protection against hunger by smoothing food consumption in chronically food insecure smallholder households through transferring resources in the form of food or cash for buying food during the ‘hunger gap’ months;
2. Prevention of impoverishment through helping households to avoid damaging ‘coping strategies’ such as selling productive assets or taking on high-interest loans to buy food;
3. Promotion of livelihoods by way of building community assets through participating people in selected public work activities that create infrastructure with developmental potential (e.g. feeder roads).

Although all of the PSNP objectives have implications for encouraging diversification as a livelihood strategy among smallholders, the promotion of livelihoods seems to have a direct relevance to climate change adaptation. This is because, the promotion of livelihoods enables households to engage in a portfolio of activities that depend less on agriculture, which is likely to be more unpredictable and risky venture due to climate change.

The majority of the beneficiaries of the programme (86.1%) are public works participants (DFID, 2009); households are allocated a labour quota of up to 30 days of work per year. The PSNP is also accompanied by a number of food security interventions that form the Other Food Security Programme (OFSP) including credit, extension, irrigation and water harvesting schemes (Hoddinott et al., 2009). In view of the above, the PSNP appears to be designed to address transfer-based and labour-based entitlement failures, for different types of rural households (Sabates-Wheeler and Devereux, 2010).

Devereux and Guenther (2009:9) identify both direct and indirect positive effects of the PSNP on livelihoods. The direct effects of PSNP are felt through the creation of employment as well as rural infrastructures such as “small-scale irrigation, micro-dams and soil and water conservation” that have the potential to increase agricultural productivity and incomes. The indirect effect of PSNP largely hinges on the regular and predictable nature of cash transfers. Such transfers, according to Devereux and Guenther (2009), raise the consumption levels of households, enhance their risk managing ability, increase investment in agriculture and facilitate the development of rural markets. All these direct and indirect effects of PSNP enable households to diversify activities. Thus, income earned from participation in public works can be invested into improving one’s agricultural output by using more inputs such as improved seeds and fertilizers (intensification) or by renting in extra land for farming (extensification). Participation in the PSNP can also facilitate non-farm activities through availing a predictable stream of income that underwrites risks in small businesses. Thus, PSNP can serve as insurance and encourage smallholders to take more risks in certain non-farm activities such as trading and craft making (Andersson et al., 2011).[56] The possible channels through which the PSNP can impact on livelihood diversification are illustrated in **Figure B** (Annexed).

[56] Moreover, PSNP can influence household decisions on migration. For example, Johnson and Krishnamurthy (2010) mention the role of transfers in covering household and labour migration expenses during agricultural slack seasons as one way by which social protection help to promote domestic and international migration. Since migration is a major source of nonfarm income in some parts of Ethiopia, it follows that the program could promote seasonal labour migration and can open-up new income earning opportunities (not least as migrants could afford to travel longer distances).

## 4. Data and Methods

Data for this study come from the Ethiopian Rural Household Survey (ERHS) that were undertaken by the Economics Department of Addis Ababa University (AAU), the Centre for the Study of African Economies (CSAE), University of Oxford, and the International Food Policy Research Institute (IFPRI). ERHS is a large panel household survey that includes about 1,477 households in 15 districts of rural Ethiopia surveyed since 1994.[57] The sample households were randomly selected from each village or Peasant Association (PA) through stratification techniques. The surveys cover four major regions (Amhara, Tigray, Oromya and SNNP) where the country's largest proportion of settled farmers are found. The ERHS surveys are of high quality with low attrition rates and have been used by several studies[58]. According to Dercon and Hoddinott (2011) the ERHS surveys can be considered as broadly representative of households in non-pastoralist farming systems although not nationally representative (see **Map 1**, Annex). This study draws on a balanced panel data of 1,306 households from the recent two rounds i.e. from the years 2004 and 2009.

### 4.1. Targeting Evaluation

One measure of the effectiveness of large-scale programmes dealing with vulnerability is targeting, which refers to how well a programme reaches its intended beneficiaries or target group. In their seminal paper, Cornia and Stewart (1993) introduced the two types of targeting errors in the implementation of large-scale programmes that intend to transfer resources to the poor. The first type of error arises when a programme fails to reach its

[57] These data have been made available by the Economics Department, Addis Ababa University, the Centre for the Study of African Economies, University of Oxford and the International Food Policy Research Institute. Funding for data collection was provided by the Economic and Social Research Council (ESRC), the Swedish International Development Agency (SIDA) and the United States Agency for International Development (USAID); the preparation of the public release version of these data was supported, in part, by the World Bank. AAU, CSAE, IFPRI, ESRC, SIDA, USAID and the World Bank are not responsible for any errors in these data or for their use or interpretation.

[58] Until, 2010 the number of publications that have used the ERHS data in their analysis have reached 303 with 77 journal articles, 4 books and 26 book chapters with more than 3000 citations (Renkow & Slade, 2013).

intended beneficiaries, which is termed as an exclusion or type I error. The second type of error occurs when a programme's resources reach to a non-target population causing resource leakages and the error is mostly referred to as inclusion or type II error.

Type I error is often measured by the proportion of individuals or households that are not reached by the programme while the share of non-poor individuals receiving programme's benefits gives a measure of type II error (see Mangiavacchi & Verme, 2013).

Galasso and Ravallion (2005) used targeting coefficient in their targeting evaluation of Bangladesh's Food-for-Education programme that combines both type I and II errors. Their coefficient is computed as a difference between the proportion of the poor and the non-poor households receiving programme benefits ranging between '1'– referring to perfect targeting with all the poor reached by the programme to '-1'– interpreted as total leakage with all transfers made to the non-poor.

We have used these targeting measures and an analysis of programme participation using a spline regression of programme participation on deciles of per capita consumption and crop income as the majority of farmers earn their income from farming.

### 4.2 Impact Evaluation

In measuring the impact of a certain programme, one often encounters the problem of selection bias that arises from either targeting criteria, or self-selection. The former is mostly referred to as "programme placement" bias, and results from effective targeting of the programme to poor communities and households while the later prescribe to the idea that people who choose to participate in the programme may be different than those with access to the programme, but choose not to participate (Gilligan et al., 2009; Khandker et al., 2010; Gertler et al., 2011). Typically, the use of randomized experiments ensures that selection bias is avoided since it compares two groups that are similar in all characteristics except participation in a programme which is randomly assigned (Caliendo & Kopeinig, 2008).These preconditions, however, are not fulfilled by the PSNP as households enrolled into the programme are selected on the basis of predefined criteria which targets chronically food insecure households. This means that apart from their participation in the PSNP, beneficiary households are likely to be systematically different from non-beneficiary households on other aspects which may affect the outcome variable resulting in a biased estimate of impact. Typically, the use of randomized experiments or Randomized Control Trials (RCTs) ensures that selection bias is avoided as it compares two groups of samples that are similar in all characteristics except participation in a programme (Caliendo & Kopeinig, 2008). However, in cases where random assignment is not possible, an evaluation has to rely on non-experimental methods to identify programme impacts.[59]

This study therefore follows a non-experimental approach in which programme beneficiaries are the treatment group and non-beneficiaries are used as a control group in order to estimate the Average Treatment Effects (ATE) of the programme. Non-experimental methods all share the notion that some assumptions have to be made in order to identify the causal effect of an intervention in the absence of an observable counterfactual (Bryson, et al., 2002; Gertler et al., 2011). A variety of non-experimental evaluation methods exist and the choice of the best strategy depends on practical considerations such as the programme's features and the type and quality of available data.

[59] This applies for most social programs that deal with poverty alleviation but even where an experiment is feasible, the implementation can be quite difficult. Often, the individuals who are randomly assigned to a control group will try to be in the treatment group if they recognize benefits creating leakage (Nichols, 2007). Moreover, RCT has limited external validity (Ravallion, 2009).

One non-experimental method used in evaluation studies is the Instrumental Variable (IV) technique. It requires identifying a variable (referred as an instrument) that is relevant for participation but not directly related to outcome variables (Bryson et al., 2002). This approach gives results similar to randomized experiments if variation in the impact of treatment is not correlated with the instrument. However, it is difficult to find an appropriate instrument in assessing the impact of large-scale programs like the PSNP, where programme participation depends on multiple factors.

The Regression Discontinuity Design (RDD), is another approach applicable for programmes where eligibility for participation is determined by the position with respect to a threshold (Khandker et al., 2010). However, this technique is not feasible for evaluating the PSNP because there is no single variable that is used as a threshold for participation. Moreover, it produces local average treatment effects that cannot be generalized for a larger context (Khandker et al., 2010).

Matching methods are also another group of non-experimental approaches. These methods can be applied to evaluate any programme or intervention outcomes as long as there is as a group that did not participate in the programme. Matching principally uses statistical techniques to artificially construct a comparison group through identifying “for every possible observation under treatment, a non-treatment observation (or set of non-treatment observations) that has the most similar characteristics possible.”(Gertler et al., 2011:107).Thus, matching methods depend on observed characteristics to construct a comparison group. Due to this, the methods require the strong assumption that there are no unobserved differences in the treatment and comparison groups that are also associated with the outcomes to be estimated. The most popular matching estimator is the Propensity Score Matching (PSM) (Becker & Ichino, 2002).

Another type of non-experimental method that is used in this study is the difference-in-differences (DID) estimator. This method compares an estimation of the outcomes of two groups of individuals (participating and non-participating) before and after implementation of a programme with the outcomes for non-participants and taking the difference as the estimate of treatment (Bryson et al., 2002). This method is widely used since it is effective in controlling unobserved variables and trends that may affect outcomes if data are available before and after an intervention (Ravallion & Chen, 2005). The validity of the estimations however, largely depends on the strong assumption that trends would have been the same in the absence of treatment for both treatment and control groups (Heckman & Smith, 1999). This assumption could be problematic if two groups display very divergent characteristics. As a result, if changes over time are a function of initial conditions that at the same time affect program participation, the DID can be biased (Jalan & Ravallion, 1998). This problem can be tackled by applying Propensity Score Matching (PSM) to match treated units with similar non-treated units on observational characteristics, then applying the DID on matched units (discussed in the next section).

This study applies the DID method combined with the PSM using the ERHS's two recent rounds of surveys that provide an ideal setting to evaluate the impact of the PSNP. These methods are discussed in detail below.

The DID addresses the selection bias in estimating the average impact of an intervention by using differences between control and experiment groups as an approximation of the counterfactual as:

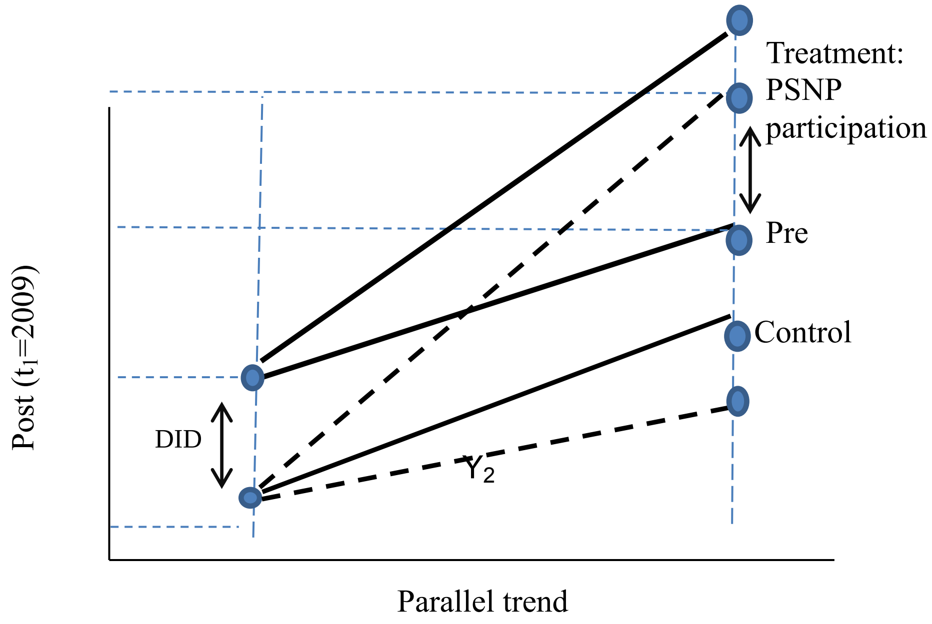
$$DID = E\left(Y_1^T - Y_0^T \mid T_1 = 1\right) - E\left(Y_1^C - Y_0^C \middle| T_1 = 0\right) \qquad (1)$$

In equation 1, $T_1$ =1 refers treatment at t=1, in our case participation in PSNP in 2009, whereas $T_1$=0 denotes lack of treatment in 2004.

The main advantage of DID estimates of treatment effects is that they remove the effect of any unobserved variables that represent time-invariant differences between the treatment and comparison group. This helps to control for the fixed components that may arise from contextual differences between beneficiary and non-beneficiary groups, such as agro-climatic conditions, markets and differences in infrastructure expansion (Gilligan et al., 2009). For instance, in the context of PSNP, if non-beneficiary households have higher average motivation than beneficiaries that is reflected in their level of income diversification, the effect of this motivation difference on measures of programme impact on income diversification is removed, when outcomes are expressed as change in income diversification.

Thus, the use of the DID method can remove bias from the unmeasured pre-program covariates, assuming that the comparison groups exhibit the same trend over time in the absence of the programme which is somehow a difficult assumption to validate (see Figure 3).

**Figure 3: A Graphical Representation of the Difference-in-Differences estimation**




One way of ensuring that the parallel trend assumption holds true for the treatment and control groups is checking if the two groups are moving in tandem before the intervention with respect to the outcome variable. As suggested by Getler et al. (2011), we have tested this assumption by plotting the trends for the pre-intervention period and ascertained that there is a strikingly parallel trend between the two groups (see **Figure C**, annexed). Another method of verifying parallel trends is to match both groups on a set of observable characteristics and then implementing the DID estimation on the matched samples. The PSM as mentioned above, serves this purpose well and provides valid estimates of programme's effect.

The PSM, to some extent, imitates the experimental context with the idea of finding a large group of non-participants who are similar to the participants in all relevant pre-treatment characteristics (Rubin, 1974; Rosenbaum & Rubin, 1983).[60] This implies estimating the counterfactual outcome by statistically constructing a valid estimate of a programme's impact for beneficiaries with what those outcomes would have been had they not received the treatment (Caliendo & Kopeinig, 2008). Finding an appropriate counterfactual constitutes the

[60] This discussion on PSM is largely drawn from a previous article (see Weldegebriel & Prowse, 2013).

main challenge of an impact evaluation (Heckman et al., 1999). This is because any programme's impact can reasonably be measured by comparing the outcomes of actual and counterfactual (a beneficiary's outcome in the absence of the intervention which cannot be observed) (Khandker et al., 2010).

Heckman, Ichimura, and Todd (1998a) and Smith and Todd (2001) illustrate how the propensity score matching constructs a counterfactual comparison group for the evaluation problem,

Let $D$ indicate whether the household receives the programme or "treatment": $D = 1$ if the household receives the programme; $D = 0$ otherwise. The evaluation problem is to estimate the average impact of the programme's intervention on those that receive it:

$$\Delta^{ATT} = E\left(\Delta \mid X, D=1\right) = E\left(Y^1 - Y^0 \mid X, D=1\right) = E\left(Y^1 \mid X, D=1\right) - E\left(Y^0 \mid X, D=1\right), \tag{2}$$

Where $X$ is a vector of control variables

This measure of program impact is generally referred to as the "Average impact of the Treatment on the Treated" (ATT).The expression $E(Y^0 \mid X, D = 1)$ represents the counterfactual outcome which is not observed and PSM provides a method for estimating this counterfactual outcome for participants by generating the probability participating in the programme (the propensity score). It then matches beneficiary and non-beneficiary units who have similar propensity scores. Specifically, PSM estimates the average impact of programme participation on participants by constructing a statistical comparison group on the basis of the probability of participating in the treatment $D$ conditional on observed characteristics *X*, given by the propensity score: *P(X)=Pr(D=1/X)* (Rosenbaum & Rubin 1983; Abadie & Imbens, 2006; Khandker et al., 2010).

A major benefit of PSM is that, unlike the regression based approaches, it uses characteristics that have not been affected by an intervention but are correlated with both the outcome and the intervention (Rosenbaum & Rubin, 1983). Moreover, the method does not require functional form assumptions for the outcome equation that is often the case for regression methods, which impose a linearity assumption which may or may not be valid (see Angrist & Pischke, 2008).

Various comparisons made between experimental methods and PSM have suggested that PSM can produce reliable and low-bias estimates if (1) treatment and control groups are drawn from the same data source; (2) treatment and control groups are exposed to similar economic incentives, such as access to markets; and (3) there are enough variables that can be used to explain outcomes and identify programme participation (Heckman et al., 1998; Bryson et al., 2002; Austin, 2011).

The approach operates with the following two assumptions:

$$E\left(Y_0 \mid X, T = 1\right) = E\left(Y_0 \mid X, T = 0\right), \text{ and} \tag{3}$$

$$0 < P\left(X\right) < 1 \tag{4}$$

The first assumption (equation 3) is called conditional mean independence. It shows that after controlling for *X,* mean outcomes of beneficiaries would be identical to outcomes of non-beneficiaries if they had not received the programme. The second assumption (equation

4) is the assumption of 'common support' given by expression (3)[61]. Common support ensures there is sufficient overlap in both treatment and control propensity score distributions (Khandker et al., 2010). Units that fall outside of the region of common support area are dropped.

The selection and inclusion of covariates to estimate a propensity score usually depends on a mix of decision criteria that includes knowledge of the programme, its targeting criteria, and previous theoretical and empirical studies. In this study, we've have considered previous impact evaluation studies on the PSNP by Gilligan et al.(2009); Hoddinott et al. (2009); Berhane et al. (2011); and our previous study Weldegebriel and Prowse (2013) to select variables for the estimation of the PSM. Moreover, we considered theoretical and practical conditions suggested by Caliendo and Kopeinig (2008) and recently by Imbens (2014).

Our analysis fulfils the conditional independence assumption by including variables in the probit model that cover the eligibility criteria for the programme but which cannot be directly affected by programme participation (see **Table A**, Annexed). Moreover, in order to control certain community and district level characteristics that might affect programme participation, such as access to markets, district and region-level dummy variables are used. Results for the probit estimations indicate that the average probability to participate in the PSNP for all the individual households in the sample is 25%. Variables such as education of household, being a male head, and age of the household head are negatively related to programme participation. These variables reflect that on average participants of the programme seem to have low human capital as compared to non-participants. Climate shocks

[61] The propensity score offers a one dimensional summary of multidimensional covariates such that when it is balanced across the treatment and control groups, the distribution of the covariates are balanced in expectation across the two groups (Nichols, 2007).

(that include an aggregate index of drought, flooding, and frost) has a positive and highly significant coefficient. As expected, such exposure to such shock is a primary factors for targeting households in the programme. Moreover, credit (loan) dummy and membership to iddir (traditional funeral service providing association) positively affect participation and have statistically significant coefficients. These variables also reflect the relative economic and social vulnerability of participants. Regional dummies– Amhara and south, have negative and significant coefficients as compared to the reference region, *Oromya. Tigray* region show a positive and significant coefficient.[62]

The assumption of common support is also fulfilled by dropping 207 households whose propensity scores lies outside the area of overlap between treatment and control groups. The distribution of the final propensity scores among the treatment and comparison groups, consisting of a panel of 1,099 households, is depicted in **Figure D** (Annexed). All results presented are based on specifications that passed the balancing tests. The propensity score is used here to match participant and control groups in the pre-program year (baseline) i.e. 2004 which is then used to estimate the DID.

## 5. Results and Discussion

### 5.1. Targeting evaluation

Like many other social protection programmes in Latin America and Africa (see Rawlings & Rubio, 2005; Slater et al., 2009), the PSNP follows both geographical and household targeting criteria. Geographically, the programme operates in 262 food-insecure districts in

[62] Participation in the PSNP is relatively high in Tigray region perhaps because the region has the most food insecure and drought affected districts and has been the epicentre of droughts, conflicts and famine which to a large extent devastated assets and agricultural potential of the region.

Tigray, Amhara, Oromiya, Southern Nations Nationalities and Peoples Region (SNNPR), Afar, Somali, rural Harari and Dire Dawa. A combination of administrative guidelines and community knowledge/participation are used in selecting beneficiaries for the household level targeting. According to the programme's implementation manual, the targets should be those chronically food insecure households from each food insecure districts.[63] The following are identified as the main criteria for beneficiary selection (World Bank, 2011):

- Chronically food insecure households that had continuous food shortages (three months of food gap or more) in the previous three years and who had received food assistance;
- Households that, in the last one or two years, suddenly became more food insecure as a result of a severe loss of assets and were unable to support themselves; and
- Households without family support and other means of social protection.

The available empirical evidences on the effectiveness of PSNP indicate that the program is well-targeted. For instance, Sharp, Brown & Teshome (2006) indicate that the use of targeting criteria such as availability of labour in the household as well as demographic characteristics helped the programme to effectively target beneficiaries. Thus, the program involved more female-headed and labour-poor households than male-headed and labour-rich households. Moreover, by doing a comparative analysis of asset holdings, Sharp et al. (2006) indicate those households that are receiving direct support from the PSNP had considerably lower average income and asset holdings such as land, than households participating in PSNP

[63] The program implementation manual also makes certain groups of a community such as the sick and the disabled, pregnant and lactating women as well as orphaned teenagers free from the obligation of participating in public works and therefore eligible for direct support. Moreover, the targeting responsibility is carried out by Food Security Task Forces or FSTFs that are organized at all levels from village to district with a bottom-up and participatory approaches followed in making decisions about targeting (Sharp et al., 2006; Farrington et al., 2007).

public works. The public works participants were also found to be poorer in incomes and asset holdings than non-beneficiary households before joining the programme.

However, Sharp et al. (2006) also note that PSNP is limited with regards to covering all food insecure households, indicating high exclusion or type I error despite the fact that it is well-targeted and minimized the inclusion error. This according to Farrington, Sharp, and Sjoblom (2007) partly emanates from the trade-off between the two types of targeting errors i.e. the inevitability of committing one error while trying to reduce the other.

They also mention that these errors of exclusion are the results of lack of resources to cover all food insecure households as well as “political pressure to graduate people quickly through the program” (ibid: IV). This finding is also corroborated by Kebede (2006) who finds pressure on graduation from food insecurity thwarts the targeting from those very poor to the relatively less poor who can show results in a short time, in two districts in Northeast Ethiopia.

In our analysis of the targeting performance of the PSNP, we have used two approaches that are widely used as targeting measures– under-coverage and leakage. Under-coverage refers to the number of people who are poor but not participating in the programme. Leakage gives a measure of the proportion of non-poor (non-target) beneficiaries that are ought to be excluded from the programme (Hoddinott, 2001; Sumarto & Suryahadi, 2001; Coady, Grosh, & Hoddinott, 2004; Mangiavacchi & Verme, 2013). Moreover, the targeting index used in Galasso and Ravallion (2005) that combines both under coverage and leakage indices is used.

**Table 1: A summary of targeting evaluation indices**

| Targeting index | Computation | Coefficient |
|---|---|---|
| Under coverage | Poor not treated/Total poor | 82 |
| Leakage | Non-poor treated/Total treated | 35 |
| Galasso & Ravallion (GR) Targeting coefficient | (Poor treated/Total poor)−(Non-poor treated/Total non-poor) | 10 |

Source: Computed from ERHS 2004–2009

The results of the under coverage corresponds to exclusion or type I error. As shown in Table 1, the PSNP fails to reach the majority of the poor in our sample. This figure however, should be taken with caution since the computation of poverty status using the binary variable often suffers from measurement error due to large confidence interval involved in the estimation. Besides, this index only relies on one variable and did not take into account other dimensions of poverty and vulnerability that reflect programme participation.

Coady et al. (2004) also assert the inevitability of the exclusion error since a programme cannot target all and employ the proportion of poor households among programme participants as a measure of targeting efficiency. After reviewing 85 anti-poverty programs, they find that this targeting measure ranges between 8 to 89 percent. The targeting efficiency using this measurement for PSNP in our sample is 65.1 % which puts it among the well-targeted anti-poverty programs in developing countries (see Coady et al., 2004). Our results on targeting performance of the PSNP is also consistent with previous findings (see Coll-Black et al., 2011).

The leakage index (type II error) is about 35 % indicating the share of non-poor benefiting from the programme in our sample. The fact that there is leakage in the program is to be expected from such a large-scale programme and for reasons that are discussed by previous studies mainly lack of resources to reach to all food insecure households (see Sharp et al., 2006; Kebede, 2006). This targeting error can be an advantage for our empirical strategy since it gives us the opportunity to have a common support region (i.e. in terms of having similar households that have in the treatment and comparison groups) and help to improve the quality of the matching and its bias reduction power.

Moreover, following Mangiavacchi & Verme (2013) we have implemented spline regression on consumption per capita deciles as well as asset holdings for the 2009 round. This analysis allows estimations on the probabilities of participating in the PSNP vis-à-vis consumption deciles. The results of the spline regression using consumption per capita and crop income (a proxy for own-production based entitlement) are presented in **Table 2**. The results show that the coefficients of the spline regressions are significant for the first decile, indicating a better targeting of this decile relative to others. The negative sign of the coefficient is interpreted as those with higher consumption have less probability to get the programme benefits. Figure 4 also show the probability of participating in the PSNP declines as consumption increases.[64] This probability is highlighted especially for PSNP participant households who earn above the minimum income of 148 ETB (30 USD), the spline regression shows a very smooth curve (**Figure E**, Annexed).

[64] These results are also verified using a different survey on the PSNP from the year 2006 that involves more participants of the program.

**Table 2: Spline Regression of PSNP participation, 2009**

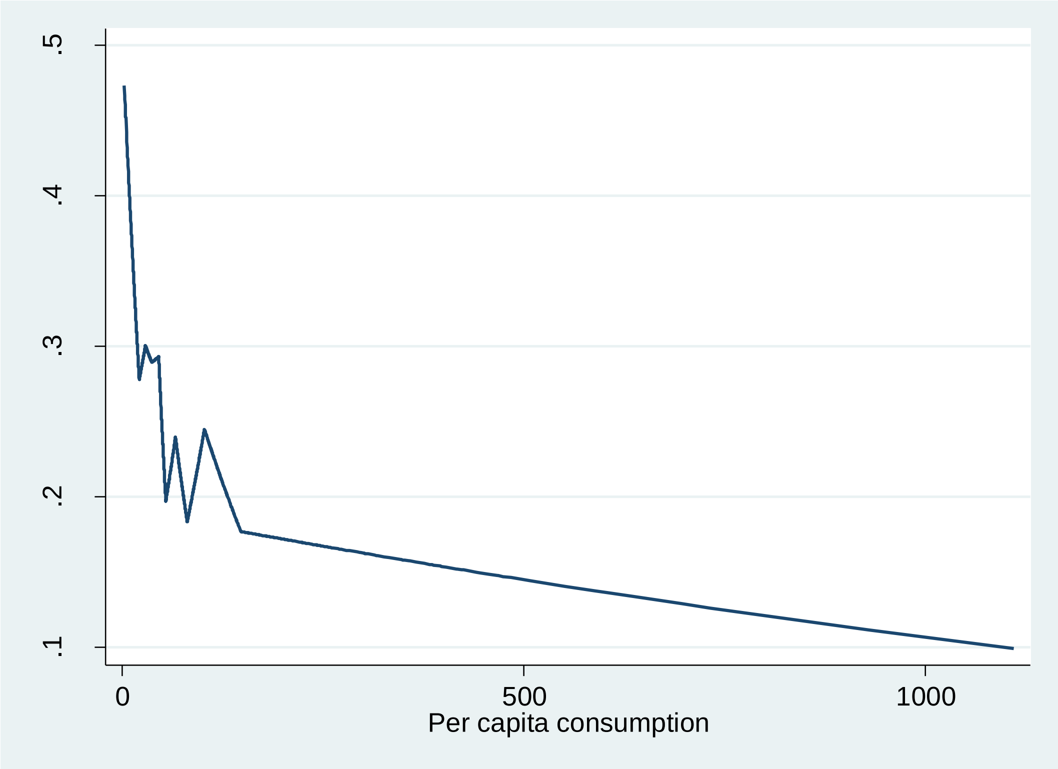
| Consumption/capita | PSNP | Crop income | PSNP |
|---|---|---|---|
| Decile 1 | -0.0438*** | Decile 1 | -0.00896* |
| | (0.00867) | | (0.00366) |
| Decile 2 | 0.0492 | Decile 2 | -0.000778 |
| | (0.0401) | | (0.00180) |
| Decile 3 | -0.0621 | Decile 3 | -0.0000115 |
| | (0.0458) | | (0.00156) |
| Decile 4 | 0.0154 | Decile 4 | -0.00163 |
| | (0.0442) | | (0.00124) |
| Decile 5 | -0.0947* | Decile 5 | 0.0000294 |
| | (0.0469) | | (0.00112) |
| Decile 6 | 0.0470 | Decile 6 | -0.000273 |
| | (0.0383) | | (0.000927) |
| Decile 7 | -0.0600 | Decile 7 | -0.000110 |
| | (0.0359) | | (0.000812) |
| Decile 8 | 0.0239 | Decile 8 | 0.000305 |
| | (0.0252) | | (0.000565) |
| Decile 9 | 0.0144 | Decile 9 | 0.00000783 |
| | (0.0121) | | (0.000208) |
| Decile 10 | -0.0125 | Decile 10 | -0.0000176 |
| | (0.00849) | | (0.0000358) |
| *N* | 1298 | *N* | 1278 |

*Standard errors in parentheses*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Computed from ERHS 2009.

**Figure 4: Spline Regression of PSNP Participation, 2009**




Source: Computed from ERHS round 7 (2009).

### 5.2. Impact of PSNP on Income Diversification outcomes

In the two surveys, households were asked questions specific to their participation in the off-farm and non-farm activities as well as the income earned from these activities both in cash and in-kind. For the matched sample of 1,099 households i.e. whose propensity scores fall within the bounds of the common support region, income earned from non-farm activities increased from 13 % in 2004 to 22 % in 2009. Off-farm income on the other hand has shown a decline from 4 % to 2 %. As would be expected in agrarian economies, the largest share of income comes from farming with a slight decline over the two survey years (see, Table E annexed). For the PSNP beneficiaries (276 households), non-farm income contributes about 29 % of their total income in 2009, while off-farm income contributes only about 1%. The income earned from public works is about 8%. Compared to the programme beneficiaries, the non-beneficiaries earn the largest share of their income from farming (77%) and less from non-farm activities (19%).

As explained in section 1, this paper follows an operational definition that distinguishes among three types of income categories– farm, non-farm and off-farm income. Farm income is obtained from crop production converted to monetary value including value of crop residue, income from the sale of animal products, and income earned from the sale of livestock. Non-farm income aggregates a range of activities that span from regular salaried non-agricultural work to self-employed activities such as trading. Income from public works is treated as an independent category and beneficiaries and non-beneficiaries are compared controlling this variable which is a direct result of the programme intervention. Moreover, income earned from renting land and oxen (rent income) as well as remittances are categorized as non-farm income. The share of income earned from different activities is provided in **Table D**, Annexed.

The DID model using the matched sample suggests that, on average, the PSNP is likely to increase annual non-farm income by up to 58.6% statistically significant at less than 1% ( see column 2 of **Table 3**). Off-farm income is likely to be significantly reduced by the programme (up to 76 %) (column 4, Table 3) while the results for farm income and overall diversification index are not significant.

**Table 3: Average impact of the PSNP on income diversification, using matched sample**

| | Diver. Index* | Non-farm income | Farm income | Off-farm income |
|---|---|---|---|---|
| ATT | 0.0074 | 0.5861*** | -0.1373 | -0.7580* |
| | (0.0199) | (0.1600) | (0.0902) | (0.3545) |
| CI | -0.0316 0.0466 | 0.2721 0.9000 | -0.3142 0.0395 | -1.455 -0.0602 |
| R.Sq | 0.1272 | 0.0988 | 0.5313 | 0.2030 |
| N | 2072 | 1424 | 2037 | 312 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:*

Income is expressed in log real annual terms based on 1994 prices.

*Diversification index is calculated as the inverse of Herfindahl index of income concentration constructed as the sum of squares of the shares of different income sources.

We have extended our analysis of the DID by adding Fixed Effects (FE) estimators. The results for non-farm income are positive and significant although the magnitude is lower while the off-farm income coefficient lost its statistical significance. The results show that on average PSNP participation is likely to increase non-farm income by 45 %, statistically significant at 5% (see **Table 4**).

**Table 4: Average impact of the PSNP on income diversification, for matched sample (FE)**

| | Farm income | Non-farm income | Off-farm income |
|---|---|---|---|
| ATT | -0.0707 | 0.4524* | -0.6769 |
| | (0.08812) | (0.1762) | (0.7822) |
| CI | -0.2437 0.1021 | 0.1060 0.7988 | -2.2682 0.9143 |
| R.sq | 0.4488 | 0.0026 | 0.0114 |
| No. groups | 1092 | 969 | 252 |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Since our focus is on non-farm income, we estimated a regression model with the two major components of non-farm income to gain more nuanced insight into the influence of the programme on non-farm activities. The results show that participation in the PSNP, on average, is likely to increase income from self-employment (own-business) by 89% compared to non-participation (see Table C column 2, Annexed). This result seems to suggest that programme participation encourages engaging in non-farm business activities perhaps by aiding in the seasonal consumption smoothing process and allowing households to use any of their savings to non-farm business ventures.

Taken together, these results on non-farm and off-farm income lend support to our schema, where an increase in non-farm income reflects a positive adaptation strategy along with a reduction in off-farm income providing evidence of positive impact of the PSNP on autonomous climate change adaptation. Similar findings have also been reported in a recent study that implemented the dose-response of PSNP participation (Berhane et al., 2011). Their conclusion is that transfers from PSNP are likely to encourage starting up of non-farm businesses.

Our result on farm income has a negative sign. This result although not statistically significant, suggests that the PSNP may not boost income from farming activities or promotes private investments in agriculture. The result is also broadly consistent with previous studies. For instance, Devereux et al. (2006), indicate cash transfers had limited impacts on on-farm investment in terms of the purchase of inputs.[65] The lack of increased farm income shown in our analysis partly could be explained by the demand for household labour in public works

[65] Devereux et al. (2006) state that out of 768 participants surveyed in 2006, 11.5% used cash transfers to purchase seeds while only 3.4% purchased fertilizers. They suggest that the main reasons for such low investment in agriculture include the low value of cash transfers and the increasing cost of food items (leaving little for investment in agriculture).

reducing availability for farm activities, a crowding-out effect (Andersson et al., 2011). Competition for labour between public works and farm activities could be especially grave if the timing for both activities overlap. Some empirical evidence suggests that PSNP can interfere with household labour for both farm and non-farm activities (for example, see Devereux et al., 2006; Slater et al., 2006). A study by Devereux et al. (2008) reported this problem in *Chiro, Fedis Kalu, Lasta* and *Kilte Awlalo* districts when there was a direct overlap in the timing between the agricultural work season and the provision of public works.

However, there is no evidence of a crowding-out effect in our analysis at least for own-business income, which has shown an increase due to programme participation. This could suggest that the crowding out effect is seasonal in nature and seems to affect only farm activities. However, due to data limitation, we cannot explore the effect of seasonality further and relied on income with the caveat that measuring income for the self or transitory employed is difficult.

Following Villa (2012) we have also combined DID with Kernel Propensity score and quintile regression. The results for the specifications of DID combining Kernel Propensity Score and quintile estimations for each category of income are summarized in **Table 5** and **6**. The Kernel Matching estimator matches all treated subjects with a weighted average of all controls using weights that are inversely proportional to the distance between the propensity scores of treated and controls (Becker & Ichino, 2002; Khandker et al., 2010).

A major advantage of the Kernel method is the use of more observations in the matching which helps to reduce the variance. However, this often comes with a price in terms of matching observations with different characters resulting in 'bad matches'(Caliendo & Kopeinig, 2008). Thus, imposing a common support condition is crucial to have a reasonable matching. To achieve this, we have implemented balancing tests on the specified covariates between control and treated groups at the baseline. The test shows that with the exception of interacted variables, all covariates have similar distributions among beneficiary (treated) and non-beneficiary (control) groups. The results reported in Table 5 have passed the balancing tests. The Kernel-DID method shows a higher coefficient of ATT for non-farm income which tends to increase by 73 % significant at less than 1%.

**Table 5: Kernel Propensity Score Matching Difference-in-Differences**

| Income Variable | Control | Treated | Diff(BL) | Control | Treated | Diff(FU) | DID |
|---|---|---|---|---|---|---|---|
| Ln farm | 6.684 | 6.733 | 0.049 | 6.861 | 7.136 | 0.275** | 0.227 |
| Std. Error | 0.077 | 0.064 | 0.101 | 0.085 | 0.064 | 0.107 | 0.147 |
| T | 86.44 | 104.63 | 0.48 | 80.3 | 110.71 | 2.57 | 1.54 |
| N | 696 | 309 | 1005 | 687 | 308 | 995 | 2000 |
| Ln non-farm | 5.44 | 5.19 | -0.24*** | 5.27 | 5.76 | 0.49*** | 0.73*** |
| Std. Error | 0.073 | 0.058 | 0.094 | 0.081 | 0.051 | 0.096 | 0.134 |
| T | 74.17 | 89.21 | -2.58 | 64.76 | 113.35 | 5.11 | 5.46 |
| N | 390 | 206 | 596 | 318 | 271 | 589 | 1185 |
| ln off-farm | 6.391 | 6.515 | 0.124 | 5.583 | 5.464 | -0.119 | -0.243 |
| Std. Error | 0.128 | 0.093 | 0.158 | 0.273 | 0.122 | 0.299 | 0.338 |
| T | 49.97 | 70.39 | 0.79 | 20.48 | 44.62 | -0.4 | -0.72 |
| N | 78 | 63 | 141 | 31 | 36 | 67 | 208 |

* Means and Standard Errors are estimated by linear regression

**Inference: *** $p<0.01$; ** $p<0.05$; * $p<0.1$ BL= Baseline, FU= Follow-up

**Table 6: Kernel Propensity Score Matching Quintile Difference-in-Differences**

| Outcome variable | DID (.10Q) | DID( .25) Q) | DID(.5 Q) | DID(.75 Q) | DID (.90 Q) |
|---|---|---|---|---|---|
| Farm income | 133.045*** | -486.384** | -775.6*** | -249.316 | 328.35 |
| | (38.99) | (-2.38) | (-3.27) | (-0.34) | (0.32) |
| Non-farm income | 27.40 | 77.75*** | 339.97*** | 433.45*** | 584.21** |
| | (1.41) | (2.74) | (4.21) | (4.35) | (2.46) |
| Off-farm income | -57.262*** | -65.89*** | 49.419 | 546.141** | 1700.29*** |
| | (-19.65) | (-27.44) | (0.70) | (2.27) | (4.67) |

*t* statistics in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Source: Computed from ERHS 2004–2009.

N.B. Outcome variables are estimated at levels without log transformations and the currency is given in ETB at 1994 prices.

**Table 6** gives the estimated coefficients for various quintiles, including the median (.5th quintile). The coefficient estimate is interpreted as the change in the median of the dependent variable corresponding to a unit change in the independent variable (Hao & Naiman, 2007). In our analysis, the coefficients are interpreted with reference to PSNP participation status accordingly; participation in PSNP on average increases farm income by 133 ETB at the 10th quintile. However, this positive effect significantly reverses at 25th and 50th quintiles and loses statistical significance towards the right tail. This result is indicative of the programme's negative impact on farm income particularly given the negative and statistically significant coefficient of the median. This significant decline means that for most participants of the programme, annual farm income on average is likely to decrease by up to 775.6 ETB (160 USD).[66] This substantial decline in farm income could lend support to the crowding-out effect of the PSNP previously discussed.[67]

[66] The average exchange rate in 1994 was 1 USD-United States [US dollar / $] =4.84 ETB-Ethiopia [Ethiopian birr]

As for non-farm income, we observe statistically significant and consistently increasing effects of programme participation as we move along the distribution. PSNP on average increases annual non-farm income at the median by about 339.9 ETB (70.25 USD) statistically significant at the 1%. This result confirms the estimations obtained from previous models.

Off-farm income quintile estimations show interesting patterns in which programme participation decreases off-farm income for those earning below the median while increasing income for those located above the median in the off-farm income distribution. This quintile results furnish a richer insight of the programme's effect on off-farm activities and income. Accordingly, for those who are already earning relatively higher income from off-farm activities, programme participation is likely, on average, to continue increasing their earnings from off-farm activities.

Since off-farm activities largely consist of activities that increase the vulnerability of smallholders to climate change shocks, this result seem to suggest that PSNP may encourage negative forms of adaptation strategies. Since this assertion has important implications for the programme's impact, it merits further investigation in terms of looking at the effect of PSNP participation on income from natural resource extraction as one component of off-farm activities that have a direct bearing on environmental sustainability and therefore implications for climate change adaptation actions. With this consideration, we have run the same Kernel propensity score matched quintile DID on income earned from the sale/extraction of natural resources component. The results are reported in Table E (Annex). These results indicate that much of the increase in off-farm income is attributable to the 'temporary agricultural labour'

[67] Given that farm income distribution is right-skewed, the median might be more suitable measure than the mean.

component as most quintiles have a positive and significant coefficients. The income earned from the extraction of natural resources (mainly in the form of charcoal making and cutting down trees for fuel wood) has for most quintiles, negative and statistically significant coefficients. These results may suggest that there is no evidence to claim that the programme encourages mal-adaptation. However one has to take caution since the results are based on few observations as the sample size dwindled by 52% from what we have in the initial estimation for off-farm income. This in turn, may have significantly increased the standard error of our estimations, making the results unreliable to drawing any firm assertion on the programme's impact on off-farm income components.

In sum, the major result of our analysis is the consistent and robust positive coefficients of non-farm income across all estimations.[68] Thus, participation in the PSNP is likely to increase a household's non-farm income ranging between 42 and 73% as compared to non-participants. This result has important implications for adapting to climate change as it suggests that the programme is contributing to smallholders' efforts to diversify into the non-farm sector and move away from depending solely on rain-fed agriculture that are extremely vulnerable to even a slight change in the climate.

[68] We checked the robustness of our findings using both the number of non-farm activities and diversification index as a measurement of livelihood diversification. The analysis showed the same positive and statistically significant results for all estimations with participation in the PSNP increasing the number of non-farm activities by at least 1 as compared to non-participation.

## 6. Conclusions

Following the 'adaptive social protection' framework discussed by Davies et al. (2013), it can be argued that the PSNP should strive to meet the following two conditions if it is to contribute to climate change adaptation:

1. A focus on transforming productive livelihoods along with protecting households;

2. A long-term perspective that takes into account the increasing vulnerability to climatic shocks.

The first condition suggests the program could shift more attention from livelihood protection to helping households to invest in productive ventures.

The second condition stipulates the need to fully incorporate climate change risks in the PSNP or other future social protection programs in Ethiopia. Supporting climate adaptation in social protection schemes requires more positive forms of income diversification than we have found in this analysis. One way of achieving this is by including the provision of livelihood packages in the form of farm inputs such as drought resistant and improved seeds, improved farm tools and skill transfers. Such schemes combined with weather index insurance can enhance the productivity and farm income of smallholders which can further lead to the expansion of the non-farm sector. Most importantly, the provision of farm input subsidies could be effective in increasing agricultural productivity of smallholders as proved by the experience of Malawi's Input Subsidy Program.[69]

As shown in our analysis, programme participation is likely to increase non-farm income for smallholder households. This has a positive implication on the impact of the PSNP in terms of encouraging activities that are relatively less climate sensitive and by extension, to climate

[69] Studies show that in Malawi, the program helped to raise maize output and substantially reduced the vulnerability of households to seasonal hunger within a short period of time (Ellis *et al*, 2009).

change adaptation. Given the small amount of income households derive from the non-farm sector (19–29%) and the dominance of farm income however, it is reasonable to assume that long-term and sustainable adaptive capacity requires reinforcing the farming sector.[70]Thus, although this has not been the topic of interest in this paper, the PSNP need to make a positive impact on farm income of beneficiaries for two interrelated reasons. First, increased farm income can be used to immediately cope with and reduce vulnerability to climatic shocks. Second, farm income is likely to create positive spill overs because smallholder-driven agricultural growth is assumed to increase demand for goods and services as smallholders are likely to use locally-hired labour, and distribute income within nearby locales, creating multipliers and thereby promoting the non-farm economy and expediting rural transformation.

[70] Even by conservative estimates, this is a very low figure since non-farm participation in the developing countries contributes about 30 percent to 45 percent of the rural household income (Haggblade et al., 2002).

**References**

Alem, Y., & Broussard, N. H. (2013). Do Safety Nets Promote Technology Adoption? Panel data evidence from rural Ethiopia.

Andersson, C., Mekonnen, A., & Stage, J. (2011). Impacts of the Productive Safety Net Program in Ethiopia on livestock and tree holdings of rural households. *Journal of Development Economics*, *94*(1), 119–126. doi:10.1016/j.jdeveco.2009.12.002

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Apata, T. G., Samuel, K., & Adeola, A. (2009). Analysis of climate change perception and adaptation among arable food crop farmers in South Western Nigeria (Vol. 22). Presented at the Contributed paper prepared for presentation at the international association of agricultural economists' 2009 conference, Beijing, China, August 16.

Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioural Research*, *46*(3), 399–424. doi:10.1080/00273171.2011.568786

Ayers, J., & Forsyth, T. (2009, July). Community based adaptation to climate change [Article]. Retrieved December 4, 2012, from http://www.environmentmagazine.org/

Barrett, C. B., Reardon, T., & Webb, P. (2001a). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331. doi:10.1016/S0306-9192(01)00014-8

Barrett, C. B., Reardon, T., & Webb, P. (2001b). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331.

Barrett, C., & Maxwell, D. G. (2005). *Food Aid After Fifty Years: Recasting Its Role*. Rutledge.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal*, *2*(4), 358–377.

Below, T., Artner, A., Siebert, R., & Sieber, S. (2010). Micro-level practices to adapt to climate change for African small-scale farmers. *A Review of Selected Literature. Environment and Production Technology Division*.

Berhane, G., Hoddinott, J., Kumar, N., Taffesse, A. S., Diressie, M. ., Yohannes, Y., & Sima, F. (2011). *Evaluation of Ethiopia's Food Security Program: Documenting Progress in the Implementation of the Productive Safety Net Programme and the Household*

*Asset Building Programme*. Retrieved from http://scholar.google.it/scholar?cluster=14541702309419314454&hl=en&as_sdt=0,5

Betts, R. A., Collins, M., Hemming, D. L., Jones, C. D., Lowe, J. A., & Sanderson, M. G. (2011). When could global warming reach 4°C? *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *369*(1934), 67–84. doi:10.1098/rsta.2010.0292

Block, S., & Webb, P. (2001). The dynamics of livelihood diversification in post-famine Ethiopia. *Food Policy*, *26*(4), 333–350. doi:10.1016/S0306-9192(01)00015-X

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science & Policy*, *12*(4), 413–426. doi:10.1016/j.envsci.2008.11.002

Bryson, A., Dorsett, R., & Purdon, S. (2002). The use of propensity score matching in the evaluation of active labour market policies [Monograph]. Retrieved December 6, 2012, from http://www.dwp.gov.uk/

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, *22*(1), 31–72. doi:10.1111/j.1467-6419.2007.00527.x

Campos, M., Velázquez, A., & McCall, M. (2014). Adaptation strategies to climatic variability: A case study of small-scale farmers in rural Mexico. *Land Use Policy*, *38*, 533–540. doi:10.1016/j.landusepol.2013.12.017

Cannon, T. (2014). Rural Livelihood Diversification and Adaptation to  Climate Change. In *Community-based Adaptation to Climate Change: emerging lessons*. Rugby: Practical Action Publising.

Carswell, G. (2002). Livelihood diversification: increasing in importance or increasingly recognized? Evidence from southern Ethiopia. *Journal of International Development*, *14*(6), 789–804. doi:10.1002/jid.924

Coady, D., Grosh, M., & Hoddinott, J. (2004). Targeting Outcomes Redux. *The World Bank Research Observer*, *19*(1), 61–85. doi:10.1093/wbro/lkh016

Coll-Black, S., Gilligan, D. O., Hoddinott, J., Kumar, N., Taffesse, A. S., & Wiseman, W. (2011). Targeting Food Security Interventions When "Everyone is Poor": The Case of Ethiopia's Productive Safety Net Programme. *IFPRI, May*.

Conway, D., & Schipper, E. L. F. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global Environmental Change*, *21*(1), 227–237. doi:10.1016/j.gloenvcha.2010.07.013

Cornia, G. A., & Stewart, F. (1993). Two errors of targeting. *Journal of International Development*, *5*(5), 459–496. doi:10.1002/jid.3380050503

Davies, M., Béné, C., Arnall, A., Tanner, T., Newsham, A., & Coirolo, C. (2013). Promoting Resilient Livelihoods through Adaptive Social Protection: Lessons from 124 programmes in South Asia. *Development Policy Review, 31*(1), 27–58. doi:10.1111/j.1467-7679.2013.00600.x

Degefa, T. (2005). *Rural Livelihoods, Poverty and Food Insecurity in Ethiopia: A Case Study at Erenssa and Garbi Communities in Oromiya Zone, Amhara National Regional State*. NTNU.

Dercon, S., & Hoddinott, J. (2011). *The Ethiopian Rural Household Surveys 1989-2009: Introduction.* (University of Oxford and International Food Policy Research Institute(IFPRI)). Oxford.

Devereux, S., & Guenther, B. (2009). Agriculture and Social Protection in Ethiopia. Retrieved from www.future-agricultures.org

Devereux, S., & Sabates-Wheeler, R. (2004). *Transformative Social Protection* (No. IDS Working Paper 232). Institute of Development Studies, Brighton, Sussex.

Devereux, S., Sabates-Wheeler, R., Slater, R., Tefera, M., Brown, T., & Teshome, A. (2008). Ethiopia's Productive Safety Net Programme (PSNP): 2008 Assessment Report. *IDS, Sussex*.

Devereux, S., Sabates-Wheeler, R., Tefera, M., & Taye, H. (2006). *Ethiopia's Productive Safety Net Programme: Trends in PSNP Transfers within Targeted Households*. Institute of Development Studies, Sussex, UK andIndak International Pvt. L. C., Addis Ababa, Ethiopia. Retrieved from http://www.ids.ac.uk/files/PSNPEthiopia.pdf

Devereux, S., & Sharp, K. (2006). Trends in poverty and destitution in Wollo, Ethiopia 1. *Journal of Development Studies*, *42*(4), 592–610. doi:10.1080/00220380600681910

DFID (2009). Building Consensus for Social Protection: Insights from Ethiopia's Productive Safety Net Programme. Retrieved December 28, 2012, from http://www.pan.org.za/node/8240

Ellis, F. (1998). Household strategies and rural livelihood diversification. *Journal of Development Studies, 35*(1), 1–38. doi:10.1080/00220389808422553

Ellis, F. (2000). *Rural Livelihoods and Diversity in Developing Countries*. Oxford: Oxford University Press.

Ezra, M., & Kiros, G-E. (2001). Rural Out-migration in the Drought Prone Areas of Ethiopia: A Multilevel Analysis1. *International Migration Review*, *35*(3), 749–771. doi:10.1111/j.1747-7379.2001.tb00039.x

FAO/WFP (2009). *Crop and Food Security Assessment Mission to Ethiopia (Phase I)*. Rome: Food and Agriculture Organization and World Food Programme.

Farrington, J., Sharp, K., & Sjoblom, D. (2007). Targeting approaches to cash transfers: comparisons across Cambodia, India and Ethiopia. *London: ODI*.

Farrington, J., Slater, R., & Holmes, R. (2004). Social Protection and Pro-Poor Agricultural Growth: What Scope for Synergies? Overseas Development Institute (ODI), Natural Resources Perspectives No. 91. Retrieved from www.odi.org.uk

FDRE (2004). *Productive Safety Net Programme: Programme Implementation Manual*. Addis Ababa: Ministry of Agriculture and Rural Development.

FDRE (2005). *Ethiopia--building on Progress : a Plan for Accelerated and Sustained Development to End Poverty (PASDEP) : (2005/06-2009/10).: Main text*. Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development.

FDRE (2010). *Productive Safety Net Programme: Programme Implementation Manual (2010)*. Ministry of Agriculture and Rural Development.

FEWS NET (2012). Ethiopia Food Security Outlook October 2012 to March 2013.

FEWS NET (2014). Ethiopia - Food Security Outlook: October 2014- to Tue, 2015-03-31 | Famine Early Warning Systems Network. Retrieved December 7, 2014, from http://www.fews.net/east-africa/ethiopia/food-security-outlook/october-2014

Fiszbein, A., Kanbur, R., & Yemtsov, R. (2014). Social Protection and Poverty Reduction: Global Patterns and Some Targets. *World Development*, *61*, 167–177. doi:10.1016/j.worlddev.2014.04.010

Galasso, E., & Ravallion, M. (2005). Decentralized targeting of an antipoverty program. *Journal of Public Economics*, *89*(4), 705–727. doi:10.1016/j.jpubeco.2003.01.002

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. (2011). *Impact evaluation in practice*. World Bank Publications.

Gilligan, D. O., Hoddinott, J., & Taffesse, A. S. (2009). The Impact of Ethiopia's Productive Safety Net Programme and its Linkages. *Journal of Development Studies*, *45*(10), 1684–1706. doi:10.1080/00220380902935907

Haakansson, M. (2009). *When the Rains Fail: Ethiopia's Struggle Against Climate Change*. Informations Forlag.

Haggblade, S., Hazell, P., & Reardon, T. (2010). The Rural Non-farm Economy: Prospects for Growth and Poverty Reduction. *World Development*, *38*(10), 1429–1441. doi:10.1016/j.worlddev.2009.06.008

Hao, L., & Naiman, D. . (2007). *Quantile Regression*. London: Sage Publications.

Hassan, R., & Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, *2*(1), 83–104.

Heckman, J. J., Ichimura, H., & Todd, P. (1998a). Matching as an econometric evaluation estimator. *The Review of Economic Studies*, *65*(2), 261–294.

Heckman, J. J., Ichimura, H., & Todd, P. (1998b). Matching As An Econometric Evaluation Estimator. *The Review of Economic Studies, 65*(2), 261–294. doi:10.1111/1467-937X.00044

Heckman, J. J., & Smith, J. A. (1999). The Pre-programme Earnings Dip and the Determinants of Participation in a Social Programme. Implications for Simple Programme Evaluation Strategies. *Economic Journal*, *109*(457), 313–48.

Hoddinott, J. (2001). 6. Targeting: Principles and Practice. *Methods for Rural Development Projects*, 89.

Hoddinott, J., Gilligan, D. O., & Taffesse, A. S. (2009). The Impact of Ethiopia's Productive Safety Net Program on Schooling and Child Labour. *SSRN eLibrary*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1412291

Imbens, G. W. (2014). *Matching Methods in Practice: Three Examples*. National Bureau of Economic Research.

IPCC (2007) *Climate Change 2007 - Impacts, Adaptation and Vulnerability: Working Group II contribution to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)*. Cambridge University Press.

IPCC (2012) *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (Special Report) (p. 582). Cambridge University Press, Cambridge, Uk and New York, NY, USA: Inter-governmental Panel on Climate Change.

Jalan, J., & Ravallion, M. (1998). *Determinants of transient and chronic poverty : evidence from rural China* (Policy Research Working Paper Series No. 1936). The World Bank. Retrieved from http://ideas.repec.org/p/wbk/wbrwps/1936.html

Johnson, C. A., & Krishnamurthy, K. (2010). Dealing with displacement: Can social protection'' facilitate long-term adaptation to climate change? *Global Environmental Change*, *20*(4), 648–655.

Kebede, E. (2006). Moving from Emergency Food Aid to Predictable Cash Transfers: Recent Experience in Ethiopia. *Development Policy Review*, *24*(5), 579–599. doi:10.1111/j.1467-7679.2006.00349.x

Khandker, S. R., Koolwal, G. B., & Samad, H. A. (2010). *Handbook on Impact Evaluation: Quantitative Methods and Practices*. World Bank Publications.

Leavy, J., & Greeley, M. (2011). Evaluation of Adaptation to Climate Change from a Development Perspective. *Evaluating Climate Change and Development*, *8*, 241.

Linnerooth-Bayer, J. (2008). International social protection for climate-related disasters. *The Irrational Economist*.

Livelihoods Integration Unit (LIU) (2011). An Atlas of Ethiopian Livelihoods. Disaster Risk Management and Food Security Sector, Ministry of Agriculture and Rural Development (MORAD). Retrieved from http://www.feg-consulting.com/spotlight/complete-atlas/Atlas%20Final%20Print%20Version%20June%2029%202011.pdf

Macours, K., Premand, P., & Vakis, R. (2012). *Transfers, Diversification and Household Risk Strategies: Experimental Evidence with Lessons for Climate Change Adaptation* (SSRN Scholarly Paper No. ID 2045949). Rochester, NY: Social Science Research Network. Retrieved from http://papers.ssrn.com/abstract=2045949

Mangiavacchi, L., & Verme, P. (2013). Minimum income in a transition economy. *Economics of Transition*, *21*(4), 683–712. doi:10.1111/ecot.12024

Nichols, A. (2007). Causal inference with observational data. *Stata Journal*, *7*(4), 507.

Osbahr, H., Twyman, C., Neil Adger, W., & Thomas, D. S. G. (2008). Effective livelihood adaptation to climate change disturbance: Scale dimensions of practice in Mozambique. *Geoforum*, *39*(6), 1951–1964. doi:10.1016/j.geoforum.2008.07.010

Paavola, J. (2008). Livelihoods, vulnerability and adaptation to climate change in Morogoro, Tanzania. *Environmental Science & Policy*, *11*(7), 642–654. doi:10.1016/j.envsci.2008.06.002

Pelling, M. (2010). *Adaptation to Climate Change: From Resilience to Transformation*. Taylor & Francis US.

Pielke, R., Prins, G., Rayner, S., & Sarewitz, D. (2007). Climate change 2007: Lifting the taboo on adaptation. *Nature*, *445*(7128), 597–598. doi:10.1038/445597a

Porter, C. (2012). Shocks, Consumption and Income Diversification in Rural Ethiopia. *Journal of Development Studies*, *48*(9), 1209–1222. doi:10.1080/00220388.2011.646990

Prowse, M., & Scott, L. (2008). Assets and Adaptation: An Emerging Debate. *IDS Bulletin*, *39*(4), 42–52. doi:10.1111/j.1759-5436.2008.tb00475.x

Ravallion, M. (2009). Evaluation in the Practice of Development. *The World Bank Research Observer*, *24*(1), 29–53.

Ravallion, M., & Chen, S. (2005). Hidden impact? Household saving in response to a poor-area development project. *Journal of Public Economics*, *89*(11), 2183–2204.

Rawlings, L. B., & Rubio, G. M. (2005). Evaluating the Impact of Conditional Cash Transfer Programs. *The World Bank Research Observer*, *20*(1), 29–55. doi:10.1093/wbro/lki001

Renkow, M., & Slade, R. (2013). *An assessment of IFPRI'S work in Ethiopia 1995–2010: Ideology, influence, and idiosyncrasy*. International Food Policy Research Institute.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. doi:10.1093/biomet/70.1.41

Rubin, D. B.(1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, *66*(5), 688–701. doi:10.1037/h0037350

Sabates-Wheeler, R., Mitchell, T., & Ellis, F. (2008). Avoiding Repetition: Time for CBA to Engage with the Livelihoods Literature? *IDS Bulletin*, *39*(4), 53–59. doi:10.1111/j.1759-5436.2008.tb00476.x

Scoones, I. (1998). Sustainable Rural Livelihoods: A Framework for Analysis. *IDS Working Paper*, *72*. Retrieved from http://200.17.236.243/pevs/Agroecologia/Sustainable%20Rural%20Livelihhods-Scoones.pdf

Sharp, K., Brown, T., & Teshome, A. (2006). Targeting Ethiopia's Productive Safety Net Programme (PSNP). *Overseas Development Institute, London and the IDL Group Ltd., Bristol*.

Sharp, K., Devereux, S., & Amare, Y. (2003). *Destitution in Ethiopia's Northeastern highlands (Amhara National Regional State)*. Institute of Development Studies at the University of Sussex.

Siegel, P. B., Gatsinzi, J., & Kettlewell, A. (2011). Adaptive Social Protection in Rwanda:“Climate-proofing”the Vision 2020 Umurenge Programme. *IDS Bulletin*, *42*(6), 71–78.

Slater, R., Farrington, J., Vigneri, M., Samson, M., & Akter, S. (2009). Targeting of Social Transfers: A review for DFID. *London: ODI*.

Smith, J. A., & Todd, P. E. (2001). Reconciling conflicting evidence on the performance of propensity-score matching methods. *American Economic Review*, 112–118.

Sumarto, S., & Suryahadi, A. (2001, June 7). Principles and Approach to Targeting:With Reference to the Indonesian Social Safety Net Program. [MPRA Paper]. Retrieved October 11, 2014, from http://mpra.ub.uni-muenchen.de/58670/

Swart, R., & Raes, F. (2007). Making integration of adaptation and mitigation work: mainstreaming into sustainable development policies? *Climate Policy*, *7*(4), 288–303. doi:10.1080/14693062.2007.9685657

Tacoli, C. (2009). Crisis or adaptation? Migration and climate change in a context of high mobility. *Environment and Urbanization*, *21*(2), 513–525. doi:10.1177/0956247809342182

The Ethiopia Observatory. (2014). Building food security in Ethiopia work in progress; new phase of PSNP agreed for 2015 -2020. Retrieved December 7, 2014, from http://ethiopiaobservatory.com/2014/07/21/building-food-security-in-ethiopia-work-in-progress-new-phase-of-psnp-agreed-for-2015-2020/

Thomas, D. S. G., & Twyman, C. (2005). Equity and justice in climate change adaptation amongst natural-resource-dependent societies. *Global Environmental Change*, *15*(2), 115–124. doi:10.1016/j.gloenvcha.2004.10.001

Van Den Berg, M., & Kumbi, G. E. (2006). Poverty and the rural nonfarm economy in Oromia, Ethiopia. *Agricultural Economics*, *35*, 469–475. doi:10.1111/j.1574-0862.2006.00192.x

Villa, J. M. (2012). *Simplifying the estimation of difference in differences treatment effects with Stata* (MPRA Paper No. 43943). University Library of Munich, Germany. Retrieved from https://ideas.repec.org/p/pra/mprapa/43943.html

Weldegebriel, Z. B., & Prowse, M. (2013). Climate-Change Adaptation in Ethiopia: To What Extent Does Social Protection Influence Livelihood Diversification? *Development Policy Review*, *31*, o35–o56. doi:10.1111/dpr.12038

Woldenhanna, T., & Oskam, A. (2001). Income diversification and entry barriers: evidence from the Tigray region of northern Ethiopia. *Food Policy*, *26*(4), 351–365. doi:10.1016/S0306-9192(01)00009-4

World Bank. (2011b). *Project Performance Assessment Report Ethiopia Productive Safety Net Project* (IEG Public Sector Evaluation No. 62549). Washington, DC: World Bank. Retrieved from http://www.oecd.org/countries/ethiopia/48503793.pdf

World Bank. (2009). *Ethiopia: Diversifying the Rural Economy. An Assessment of the Investment Climate for Small and Informal Enterprises* (MPRA Paper). Retrieved from http://mpra.ub.uni-muenchen.de/23278/

World Bank. (2010). *Economies of Adaptation to Climate Change: Ethiopia*. Washington, DC. Retrieved from http://climatechange.worldbank.org/sites/default/files/documents/EACC_Ethiopia.pdf

Zorom, M., Barbier, B., Mertz, O., & Servat, E. (2013). Diversification and adaptation strategies to climate variability: A farm typology for the Sahel. *Agricultural Systems*, *116*, 7–15. doi:10.1016/j.agsy.2012.11.004

## Annex

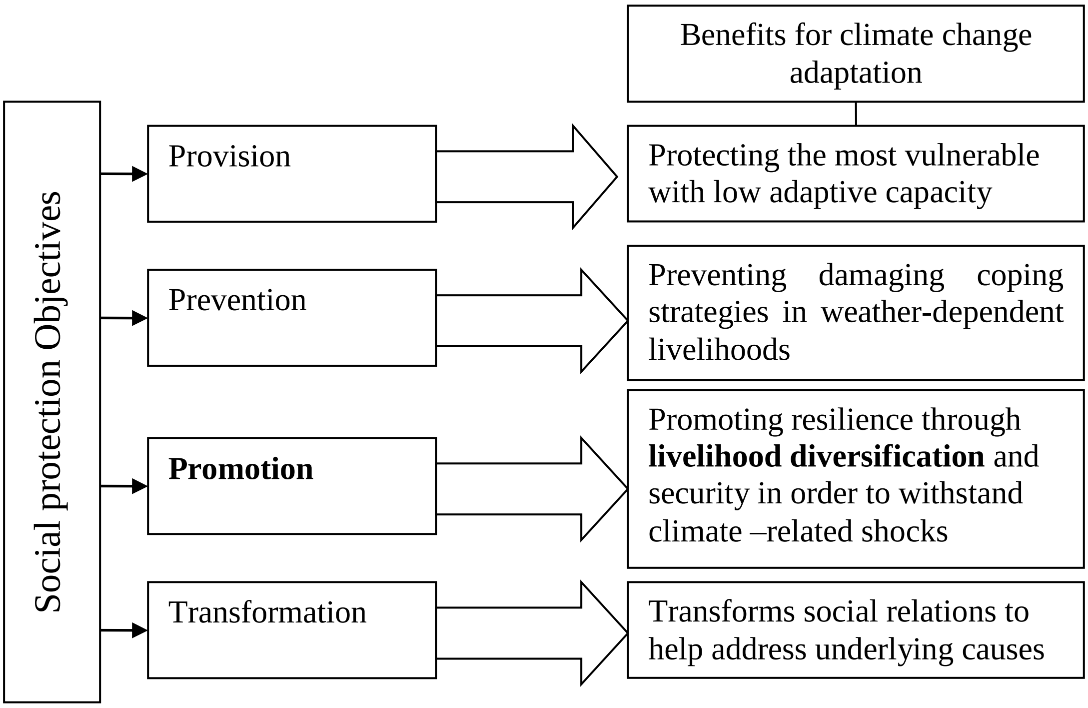
**Table A: Probit Estimations of Variables used in the PSM**

| | |
|---|---|
| Age of household head | -0.06 |
| | -0.03 |
| Age of household head (sqrt.) | 0.53 |
| | -0.45 |
| Male head (=1) | -0.756$^{*}$ |
| | -0.31 |
| Education of household head | -0.035$^{*}$ |
| | -0.02 |
| Dependency ratio | -0.18 |
| | -0.19 |
| Household size | -0.13 |
| | -0.11 |
| Poor dummy (=1) | 0.17 |
| | -0.13 |
| Livestock holding (tlu) | -0.01 |
| | -0.03 |
| Number of oxen | -0.12 |
| | -0.06 |
| Loan taken dummy (credit) | 0.17 |
| | -0.09 |
| Participation in Iddir dummy (=1) | 0.62$^{***}$ |
| | -0.19 |
| Land size ( in ha) | -0.41$^{*}$ |
| | -0.16 |
| Land size (sqrt.) | 1.05$^{**}$ |
| | -0.38 |
| Climate shock index | 0.46$^{***}$ |
| | -0.09 |
| Asset index | -0.19 |
| | -0.29 |
| Ln crop income | -0.04 |
| | -0.03 |
| Ln consumption per capita | 0.00 |
| | -0.09 |
| _cons | -2.19 |
| | -1.68 |
| *N* | 1888.00 |
| chi2 | 841.40 |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$

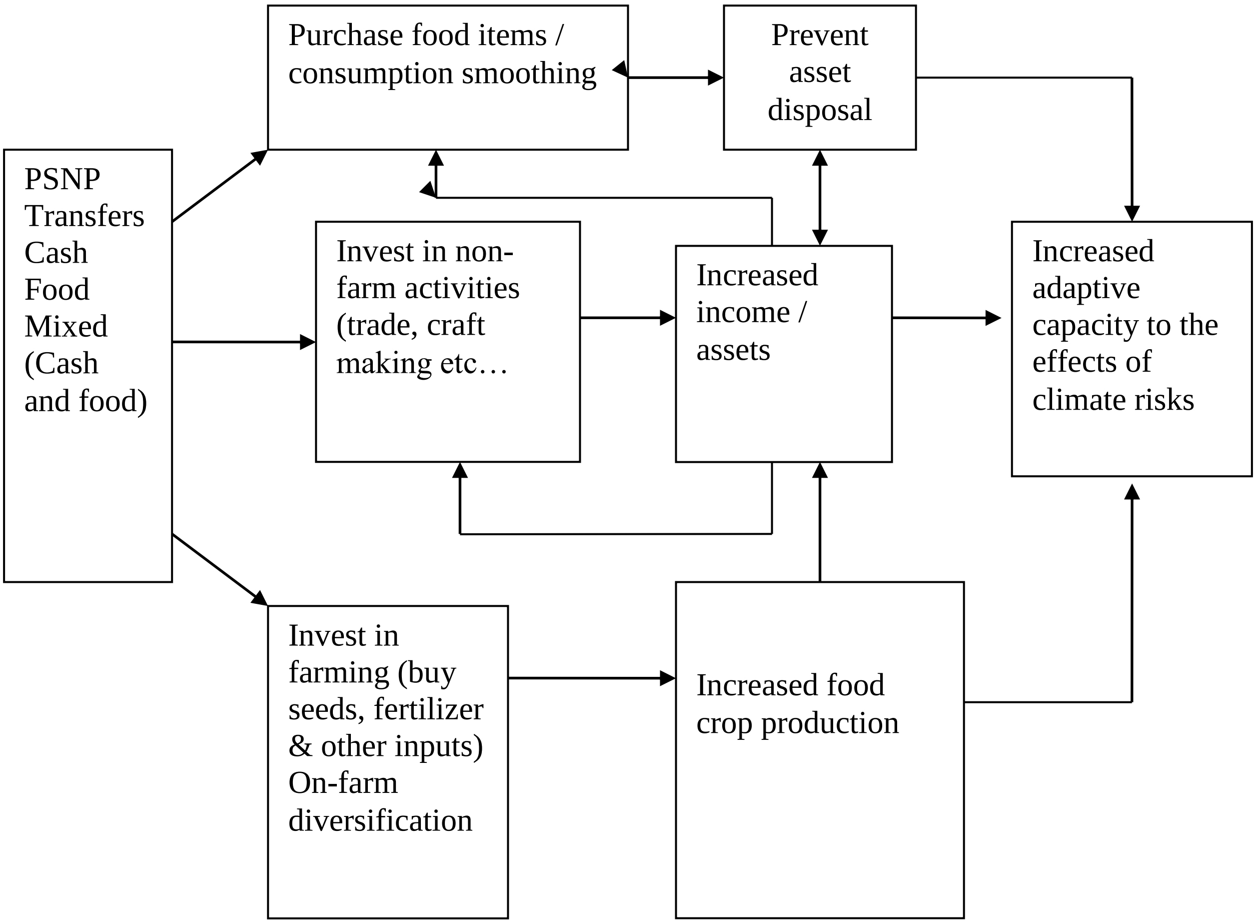
Source: computed from ERHS 2004–2009.

**Figure A: Social protection and its benefits for climate change adaptation**




Source: Devereux and Sabates-Wheeler (2004) and Davies et al. (2008).

**Figure B: Analytical framework on the possible impacts of PSNP on livelihood diversification in Ethiopia**




Source: Weldegebriel and Prowse (2013), adapted from Devereux (2002)

**Table B: Average impact of the PSNP on non-farm and off-farm income categories, using matched sample**

| | Non-farm wage employment | Non-farm self-employment | Sale of natural resources | Temporary agricultural labour |
|---|---|---|---|---|
| ATT | -.3466<br>(-0.73) | .8945*<br>(2.44) | -.3362<br>(-0.88) | -.4864<br>(-0.87) |
| R.Sq | 0.2605 | 0.1890 | 0.1368 | 0.2886 |
| N | 251 | 503 | 139 | 143 |

*t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: computed from ERHS 2004–2009.

**Table C: Mean income composition from major sources 2004–2009**

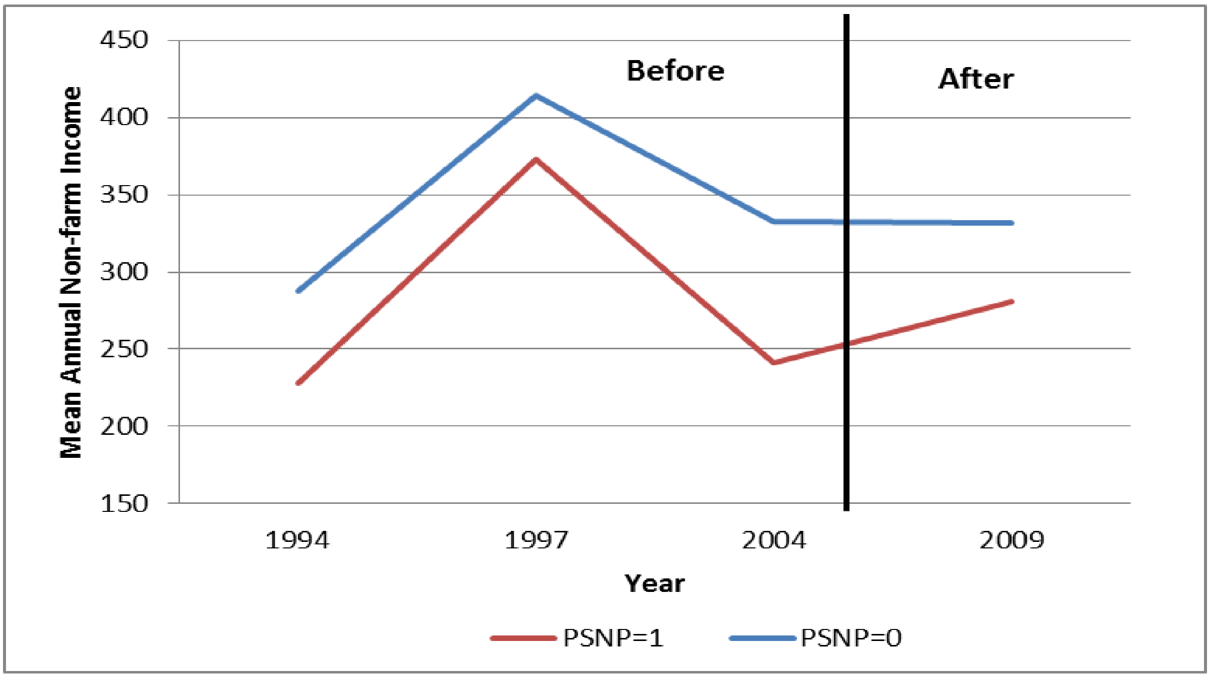
| Year | Crop | Livestock | Non-farm | Off-farm | Non-farm wage | Non-farm own business |
|---|---|---|---|---|---|---|
| 2004 | 2047.16 | 562.85 | 657.37 | 375.28 | 359.60 | 293.77 |
| 2009 | 2333.05 | 372.63 | 574.83 | 230.20 | 236.00 | 163.73 |
| Participants | 2201.47 | 261.00 | 414.38 | 226.81 | 126.25 | 126.63 |
| Nonparticipants | 2370.776 | 418.31 | 754.43 | 230.99 | 380.83 | 168.86 |

Source: computed from ERHS 2004–2009.

*Notes:*

Income is expressed in mean annual terms based on 1994 prices.
Crop income includes the monetary value of all crops produced in Meher and Belg seasons
Livestock income includes income earned from the sale of live animals (not because of distress sale that has adverse effect on asset holding) and income from animal products such as milk, cottage cheese, meat, hides and skins etc. The 1994 round does not include income from the sale of animal products as it was not reported in the data.
Non-farm wage income is composed of income earned from the following sources as reported in the data: Professional (Teacher, government worker), skilled labourer (Builder, Thatcher), Soldier, driver/Mechanic, unskilled non-farm worker, domestic servant, and guard.
Non-farm self-employment largely constitutes income earned from own-business activities such as Weaving/spinning, milling, handicraft, including pottery, trade in grain/general trade, income from services such as traditional healer/religious teacher, transport (by pack animal), selling injera and wett (food),Barbary and tailoring. It also includes the making and selling of local drinks, carrying goods, builder (masonry), making roof for houses, rock splitting, and fruit and vegetable vending.

**Figure C: Trends of beneficiaries and non-beneficiaries before and after the programme**




Source: computed from ERHS 1994–2009.

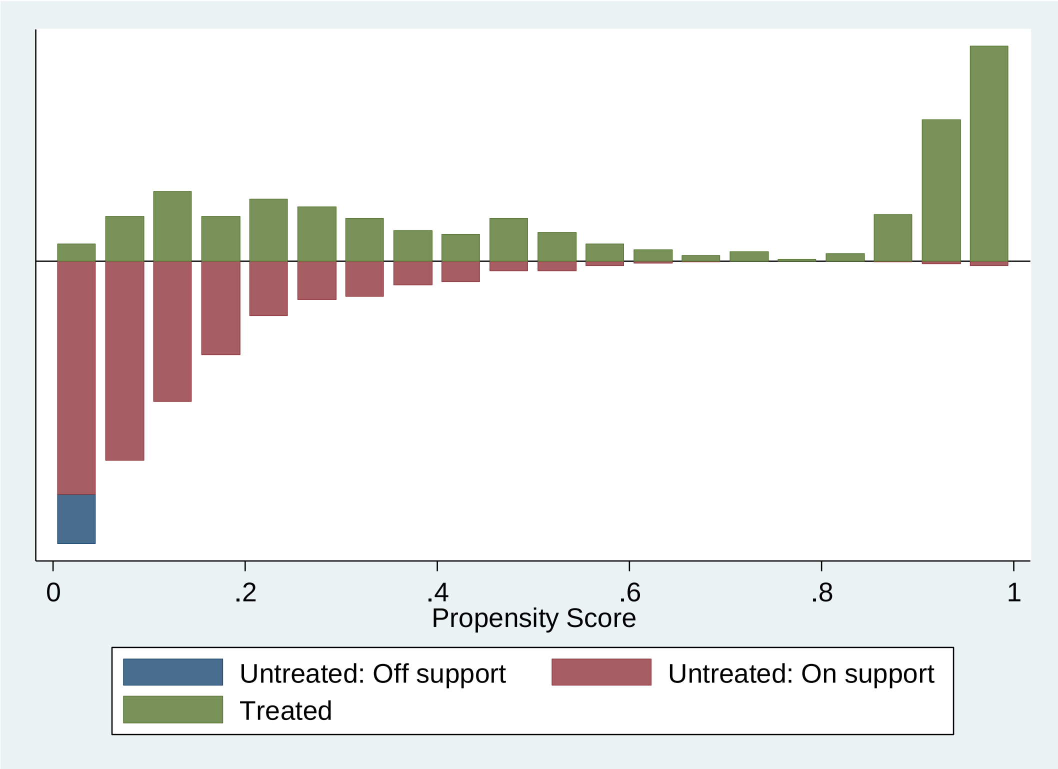
*Note:*

This trend analysis is one of the falsification tests of the parallel trend assumption for the DID. The two groups have similar non-farm income trends before the programme.

PSNP=1 refers to programme participants

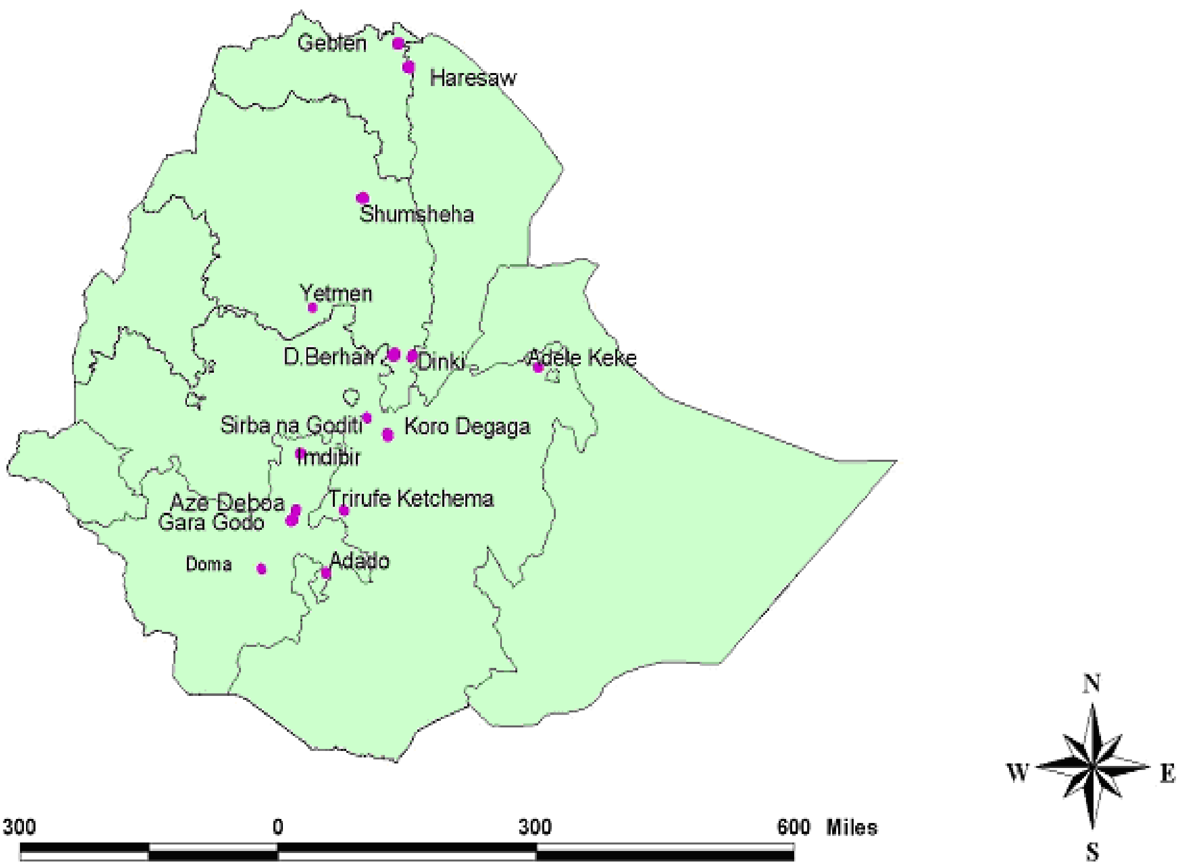
PSNP=0 refers to non-participants of the programme

**Figure D: Propensity score distribution among treatment and comparison observations**




Source: computed from ERHS, 2004–2009

**Map 1: Peasant Associations/villages surveyed in the ERHS dataset**




Source: Dercon and Hoddinott (2011)

**Table D: The share of income from different categories, 2004 and 2009**

| year | farm share | non-farm share | off-farm share | Public works | Others | Total |
|---|---|---|---|---|---|---|
| 2004 | 0.79 | 0.13 | 0.039 | – | 0.036 | 1 |
| 2009 | 0.73 | 0.22 | 0.02 | 0.02 | 0.006 | 1 |
| PSNP participants | 0.62 | 0.291 | 0.0126 | 0.073 | 0.001 | 1 |
| Non-participants | 0.77 | 0.194 | 0.0286 | – | 0.009 | 1 |

Source: Calculations from ERHS 2004–2009.

*Note:*

Emergency food aid was the standard response for a long time prior to the launching of PSNP in 2005.

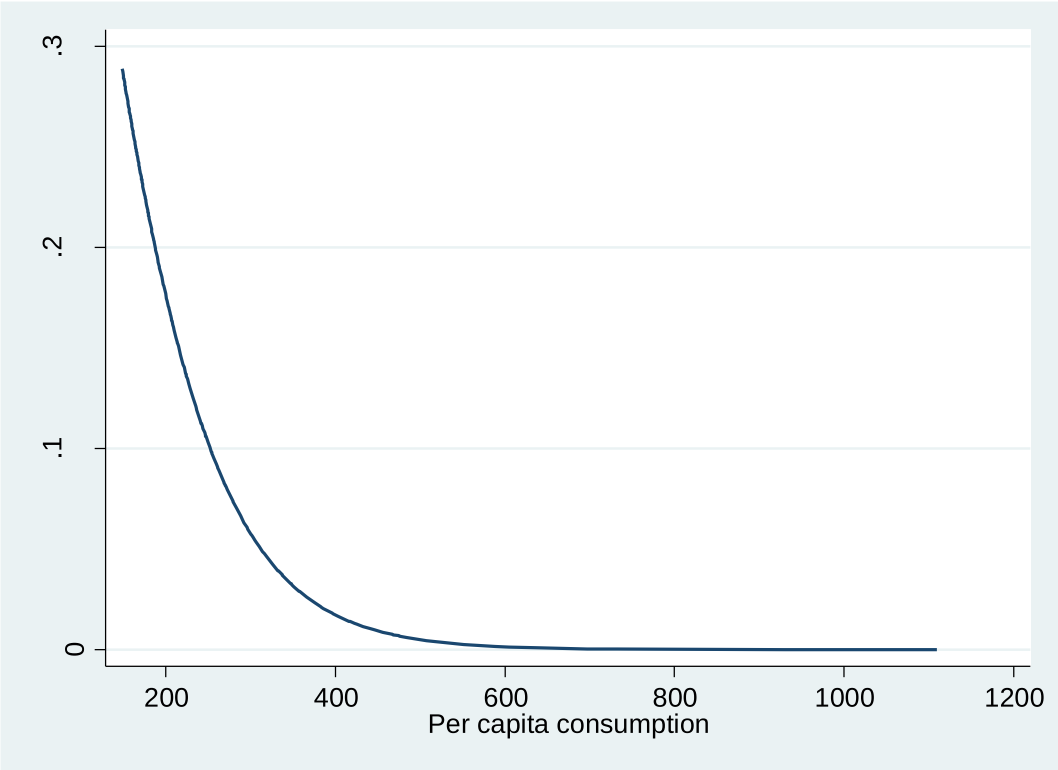
**Table E. Kernel Propensity Score Matching Quintile DIDs for off-farm income categories**

| Agricultural labor | ATT | Sale of natural resources | ATT |
|---|---|---|---|
| Quintile 1 | 2.318 | Quintile 1 | -104.7 |
| | (0.02) | | (-1.35) |
| Quintile 2 | 135.8*** | Quintile 2 | -129.3*** |
| | (2.69) | | (-5.91) |
| Quintile 3 | 181.17*** | Quintile 3 | -268.16*** |
| | (2.80) | | (-16.27) |
| Quintile 4 | 179.74** | Quintile 4 | -290.85*** |
| | (2.35) | | (-171.91) |
| Quintile 5 | 586.2*** | Quintile 5 | -231.4*** |
| | (7.68) | | (-7.86) |
| Quintile 6 | 565.13*** | Quintile 6 | -308.1*** |
| | (8.23) | | (-8.72) |
| Quintile 7 | 344.58*** | Quintile 7 | -196.91*** |
| | (3.19) | | (-2.88) |
| Quintile 8 | 1370.03*** | Quintile 8 | -127.10 |
| | (5.68) | | (-0.86) |
| Quintile 9 | 1251.58 | Quintile 9 | 64.84 |
| | (1.20) | | (0.53) |
| No. control | 60 | N control | 46 |
| No. treated | 46 | N treated | 68 |
| Total | 106 | Total | 114 |

*t* statistics in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Source: calculations from ERHS 2004–2009.

**Figure E: Spline function of PSNP participation for consumption per capita (>148 ETB)**




Source: Computed from ERHS round 7 (2009)