Social Protection and Vulnerability to Climate Shocks: a Panel Data Evidence from Rural Ethiopia

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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 role of the Productive Safety Net Program in reducing vulnerability to climate related shocks and its impacts on autonomous adaptation strategies by taking the case of household income diversification into non-farm activities. The paper assesses vulnerability using index-based approach and the impact of the program using two 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 for the years 2004 and 2009. Taking advantage of the extensive data available on climate-induced shocks and 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 program. The results from the vulnerability assessment indicate that exposure and lack of adaptive capacity to climate-induced shocks explain the vulnerability of rural households and PSNP helps to decrease the vulnerability of households to climate-induced shocks. The results from the non-experimental estimations also indicate that receiving transfers from the PSNP, on average increases income from non-farm activities. These results partly confirm the hypothesis that social protection can promote positive adaptation strategies and may serve as an effective means of reducing the vulnerability of smallholders to climate change-induced shocks.

Keywords: climate change, difference-in-differences, diversification, Ethiopia, social protection, vulnerability

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Introduction

Social protection 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 et al. 2014; Barrientos and Hulme 2016). Many Social protection 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 programs in addressing climate-related shocks and vulnerabilities as well as in creating more inclusive and sustainable development pathways (World Bank 2010; Bene et al., 2012; Macours et al. 2012; Piece 2012; Davies et al. 2013; Mesquita et al. 2016).

However, little empirical evidence exists about the extent and conditions by which social protection schemes are able to contribute to addressing environmental challenges such as climate change at household and community levels. 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 and Raes, 2007).Thus, given the magnitude of the projected impacts of climate change on Ethiopia (Haakansson, 2009; Conway and Schipper 2011), there is a need to evaluate to what extent the existing social protection scheme i.e. the Productive Safety Net Program (PSNP) contributes to reducing vulnerability to climate related shocks.

Moreover, the projected impacts of climate change also pose important questions for the implementation of social protection schemes (Davies et al.2009; Conway and 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 livelihood diversification, which helps households build resilience in the face of various shocks (Ellis 2000; Barrettet al. 2001; Haggblade et al. 2010; Macours et al. 2012; Zorom et al. 2013). While it has long been recognized that livelihood diversification is an important strategy for adapting to climate change at household level (see Prowse and Scott 2008; Sabates-Wheeler et al. 2008; Campos et al. 2014; Tanner et al. 2015)there is little empirical evidence on interventions that may help promote such strategies in the context of adapting to climate change. Despite the strong theoretical appeal for integrating social protection and climate change responses, the lack of empirical evidence on the role of social protection as a response to the climate change challenge hampers informed policy making.

This study is motivated to bridge the existing gap in the literature and aims to examine (1) the potential role of social protection in reducing vulnerability to climate related shocks in Ethiopia and (2) the possible links between participation in the PSNP as the main social protection scheme and diversification by smallholders, which is considered as a major autonomous adaptation to climate change in Africa (Below et al. 2010).

The rest of this paper is structured as follows. Section 2 provides a concise review of the existing literature on the issues of climate change, livelihood vulnerability and diversification as a case of autonomous adaptation strategy to climate change as well as a description on the PSNP. Section 3 outlines the empirical method and data used to estimate the role of PSNP in addressing climate-related vulnerability and its impact on autonomous adaptation. Section 4 presents and discusses the results from vulnerability assessment and impact evaluation estimates. Section 5 concludes with some policy recommendations.

Literature Review

Rural livelihoods often involve risks and uncertainties, which tend to change through time and space as a result of the interplay among several factors. These risks and uncertainties come from both natural and human activities and directly or indirectly affect the specific strategies that people employ at national, community or household levels to sustain their livelihoods (Marschke and Berkes 2006;Blaikie et al. 2014). Thus, rural livelihoods are exposed to multitudes of shocks and stresses that form the ‘vulnerability context’ of livelihood systems, which in turn determine the livelihood conditions of people. One source of external shocks and stresses to peoples’ livelihoods is the natural environment, upon which the majority of rural people in developing countries depend for their subsistence (Blaikie et al. 2014). Clearly, such dependence on the natural resource base, makes people more vulnerable to the vagaries of nature. Thus, extreme climatic events such as drought and flooding often turn into disasters and pose major livelihood risks to people. This is particularly evident in Ethiopia where poverty and food insecurity have long been associated with the onset of extreme natural events, such as droughts, that together with socio-economic and political factors, were noted to be easily transformed into major livelihood crisis such as famine (Belayneh 2003; Belayneh et al. 2013).

Autonomous Adaptation to Climate Change

There is a growing consensus in the literature that adaptation measures are the most viable response to climate change in poor countries (Pielke et al. 2007; Ayers and Forsyth 2009). This is so as the current efforts at mitigation may take more time to implement with a subsequent delay in reducing the problem of global warming. In contrast, adaptation strategies are more tangible and applicable as most activities consist of measures that are geared towards lessening both the short and long-term impacts of climate change on economies, people and their livelihoods (Leavy and Greeley 2011).

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 strategies while coping is temporary adjustments in the face of change". 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.

Diversification and Adaptation

Diversification can have both positive impacts in terms of making livelihoods more secure and reducing the adverse impacts of seasonality through, for example, consumption smoothing, risk reduction, complete use of available household labour and skills, and cash generation for investment in human or physical capital (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 Bank2009). 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). Bryan et al. (2009) confirm the positive role of non-farm activities and income in their study on the determinants of adaptation to climate change in Ethiopia and South Africa. They found that next to basic household and demographic characteristics, non-farm income is identified as having the most positive effect in encouraging adaptation options to climate change in agricultural livelihoods.

This paper follows the frequent distinction between diversification for necessity and diversification by choice (Hart 1994, cited in Ellis 1998) and defines the relationship between diversification and climate adaptation in two ways. First increased non-farm income is viewed as positive adaptation. Second, by applying a strict definition of off-farm activities as temporary farm wage or in-kind employment, as well as collection of natural resources, an increase in off-farm income is considered as an indicator of distress and therefore a negative form of adaptation.[2]

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).[3]

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 epicentres 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 60% of households' income in some parts 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. Tassew and Oskam (2001) in their study in Tigray in North Ethiopia, show that households diversify into non-farm activities

[2]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).

[3]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).

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 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).

Adaptive Social Protection and the PSNP

Various studies indicate that social protection play significant roles in promoting productive investment, increase the resilience of households to shocks, enhance the risk taking and entrepreneurial abilities of poor people; and help to smoothen consumption (Devereux and Sabates-Wheeler 2004; Davis et al.2009; Bene et al. 2012).

A recent literature suggests that social protection programs 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 et al. 2011; Davis et al. 2013; Barrientos and Hulme, 2016). 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 programs 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 also help to transform livelihoods. Social protection is also integrated in the Sustainable Development Goals (SDGs) as many of the measures or activities involved in social protection programs are directly related to the first goal about hunger and poverty and are included as a policy area to achieve the equality goal. In this regard, Steinbach et al. (2016) through a case study from India's north-western state of Rajasthan showcase the benefits of aligning social protection and climate change interventions in enabling households to manage risks, reduce poverty and promote climate-resilient livelihoods. They argue that "[S]ocial protection and climate change interventions both seek to build the resilience of poor and climate vulnerable households by strengthening their capacity to absorb and/or transfer risks" (Steinbach et al. 2016: 11).

Social protection in Ethiopia is inextricably linked to policy measures taken to address the persistent problem of food insecurity (Dessalegn et al. 2013).[4] The Productive Safety Net Program (PSNP) initiated by the Government of Ethiopia and a group of donors in 2005 is designed to address the needs of food insecure households through 'multi-year predictable resource transfers' rather than emergency humanitarian aid (FDRE 2004).[5] The PSNP is possibly the largest social protection scheme in sub-Saharan Africa with an estimated 7.6 million

[4]Since the mid-1980s, the country has relied on emergency interventions to meet national food deficits (FDRE 2005). However, such interventions were rendered ineffective due to recurrent droughts, resulting in a gradual deterioration of households' food security status (Barrett and Maxwell 2005).

[5] 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).

beneficiaries enrolled in 2012, or eight percent of Ethiopia's population. The program is now in its fourth phase with an estimated maximum annual caseload of 10 million clients (Program Implementation manual (PIM) 2014). PSNP 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 program 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). The Public Works component of the PSNP transfer cash or food and create rural infrastructure; second, the Household Asset Building Program, which has been part of the Food Security Strategy of the FDRE since 2010, helps to promote agricultural and non-agricultural livelihoods through asset transfers, extension services and subsidized credit (Devereux 2016).

The PSNP primarily aims to strengthen resilience, improve nutrition, and help households become food sufficient and, eventually, food secure and according to the latest program implementation manual, through the provision of technical assistance and training in livelihood activities (crop and livestock, off-farm, and employment) the program aims to support households to increase and diversify their incomes and build their assets (PIM 2014:19).

Thus, by espousing the promotion of livelihoods, the program 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. Moreover, the majority of the beneficiaries of the program (86.1%), being public works participants (DFID 2009) and the program being accompanied by a number of food security interventions form the Other Food Security Program (OFSP) including credit, extension, irrigation and water harvesting schemes (Hoddinott et al. 2009), means that it can 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).

Data and Methods

Data for this paper come from the Ethiopian Rural Household Survey (ERHS) that were undertaken by the Department of Economics 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.[6] 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 SNNPR) 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. 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. This paper draws on a balanced panel data of 1,306 households from the recent two rounds i.e. from the years 2004 and 2009.

Estimating Vulnerability to Climate-Induced Shocks

The concept of vulnerability can be viewed as an interaction between peoples' capabilities determined by their socio-economic positions and their exposure to hazardous events (Cannon 2006). This highlights that vulnerability should be

[6]These data have been made available by the Department of Economics, Addis Ababa University, and 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.

analyzed as having differential impacts on people's livelihood. In the context of climate change, the assessment of vulnerability mainly involves tools that are used to assess the vulnerability of a community and its natural resources to climate change. The approach is recommended in much of the recent climate literature and it is thought to include exposure, sensitivity, and adaptive capacity that jointly determine the level of vulnerability to climate change impacts (Adejuwon et al. 2012; Marshall et al. 2014; Aberman et al. 2015). Exposure refers to the extent to which a community comes into contact with climate events or specific climate impacts. This mainly includes location and resource use that are exposed to different climate events and impacts. Sensitivity captures the degree to which a community is negatively affected by changes in climate. This is largely determined by the relationship of individuals, households, or a community to resources impacted by climate events, and by the degree of dependency on those resources. The third component, adaptive capacity refers to the potential of a household or a community to adjust to the impacts of changing climate. Within the context of livelihoods, diversification as one strategy contributes to the reduction of vulnerability as it strongly relates to the sensitivity and adaptive capacity components. For example, a household that has diversified sources of income and supplementary livelihood options will likely have higher adaptive capacity to impacts of climate change than those that do not, indicating that diversification can be a critical adaptation strategy to climate change impacts.

This paper adopts the Livelihood Vulnerability Index (hereafter referred to as LVI) developed by Hahn et al. (2009) to measure the vulnerability of households to climate-related shocks, mainly drought and flood. This LVI measurement largely fits to the study context and helps to capture the key factors that reflect the vulnerability situation of smallholder farmers in the face of climate induced environmental hazards. Similar to the LVI used in Hahn et al. (2009), this paper employed nine key variables, which relate to socio-demographic characteristics (SDC) (household size, dependency ratio, age, gender of household head, education and participation in social networks (*iddir*), livelihood strategies (LS) (diversification index), health status (HS), access to water (AW), access to electricity (AE), social network (SN), and climate-induced shocks (CS) (consisting drought, flood and frost). Moreover, following Madhuri et al. (2014) and in line with the Sustainable Livelihood Framework (SLF)[7] (Birkmann 2006;

[7]The concern of livelihood approach is to understand how different people in different places live (Scoones 2009). Apart from being an analytical tool, SLF takes vulnerability as a comprehensive concept covering livelihood assets and their access, and vulnerability context elements (i.e., shocks, seasonality, and trends) as well as institutional structure and processes (Birkmann 2006).

Scoones 2009). This paper further included natural capital (NC) (captured by land size index) and fiscal capital (FC) that refers to possession of livestock measured in Tropical Livestock Unit (TLU).

Computing the LVI

The dimensions of vulnerability were systematically combined with equal weights to create an index on a scale of 0 to 1. As in the case of the computation of the life expectancy index of the Human Development Index (HDI), the computation of each indicator of the vulnerability index followed the process of standardization (Hahn et al. 2009).

$$I_a = \frac{S_a - S_{\min}}{S_{\max} - S_{\min}} \qquad (1)$$

Where, I_a is the standardized value of each indicator. S_a the original subcomponent for household a, $S_{\min}$ is the minimum value of the indicator across all households, and $S_{\max}$ is the maximum value of the indicator across all households. After each indicator was standardized, the average value of each component was calculated using equation 2:

$$M_a = \frac{\sum_{a=1}^{n} I_{a^i}}{n} \qquad (2)$$

Where M_a is the one of the eight components for household a, I_{a^i} indicates the sub-components indexed by i, which builds each major component, and n is the number of sub-components of each major component. After obtaining values for each of the eight components, the household level LVI was obtained by combining these components using equation 3:

$$LVI_a = \frac{\sum_{i=1}^{8} w_{M_i} M_{a^i}}{\sum_{i=1}^{8} w_{M_i}} \qquad (3)$$

Which can be further expressed as:

$$LVI_a = \frac{w_{SDC} SDC_a + w_{LS} LS_a + w_{HS} HS_a + w_{AW} AW_a + w_{AE} AE_a + w_{SN} SN_a + w_{CS} CS_a + w_{NC} NC_a + w_{FC} FC_a}{w_{SDC} + w_{LS} + w_{HS} + w_{AW} + w_{AE} + w_{SN} + w_{CS} + w_{NC} + w_{FC}}$$

……(4)

Where LVI_a, is the Livelihood Vulnerability Index for household a, which equals the weighted average of eight major components, w_{M_i} .The weights of each major component are given by the number sub-component that make up each major component, which are used to guarantee that all sub-components have equal contribution to the total LVI (Hahn et al. 2009). The LVI value ranges between 0 and 1, where 0 denotes the least vulnerable while 1 implies the most vulnerable (Etwire et al. 2013; Madhuri et al. 2014). Equation 4 is estimated by pooling observations for 2004 and 2009.

Estimating the Impact of PSNP on Diversfication

This study follows a non-experimental approach to estimate the impact of PSNP on autonomous climate change adaptation. In this approach, program beneficiaries are used as the treatment group and non-beneficiaries are used as a control group in order to estimate the Average Treatment Effects (ATE) of the program. In the use of non-experimental methods, 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 program's features and the type and quality of available data**.**

One type of non-experimental methods is the difference-in-differences (DID) estimator that compares an estimation of the outcomes of two groups of individuals (participating and non-participating) before and after implementation of a program 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 available before and after an intervention (Ravallion and 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 and 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 and Ravallion 1998). This problem can be overcome 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.

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:

$$DID = E\left(Y_1^T - Y_0^T \mid T_1 = 1\right) - E\left(Y_1^C - Y_0^C \middle| T_1 = 0\right) \quad (5)$$

In equation 5, T_1 =1 refers to 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 program 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 program which is somehow a difficult assumption to validate.

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 Gertler et al. (2011), this assumption is tested by plotting the trends for the pre-intervention period and ascertained that there is a strikingly parallel trend between the two groups (see **Figure 1**). 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 program's effect.

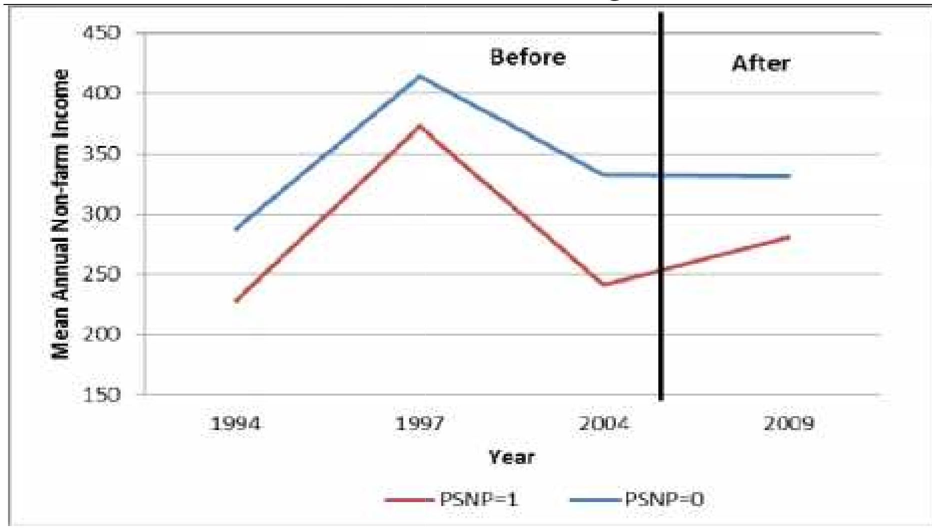


Figure 1. Trends of beneficiaries and non-beneficiaries before and after the program
Source: computed from ERHS 1994–2009
Note: This trend analysis is one of the falsification tests of the parallel trend assumption for the DID. The two groups have similar non-farm income trends before the programme.

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 and Rubin 1983). This implies estimating the counterfactual outcome by statistically constructing a valid estimate of a program's impact for beneficiaries with what those outcomes would have been had they not received the treatment (Caliendo and Kopeinig 2008).Finding an appropriate counterfactual constitutes the main challenge of an impact evaluation (Heckman et al. 1999). This is because any program'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, Koolwal, and Samad 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 T indicate whether the household receives the program or "treatment": $T = 1$ if the household receives the program; $T = 0$ otherwise. The evaluation problem is to estimate the average impact of the program's intervention on those that receive it:

$$\alpha^{ATT} = E(\alpha \mid X, T=1) = E(Y^i - Y^0 \mid X, T=1) = E(Y^i \mid X, T=1) - E(Y^0 \mid X, T=1) \quad (6)$$

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 $E(Y^0 \mid X, \mathrm{T} = 1)$ 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 program (the propensity score). It then matches beneficiary and non-beneficiary units who have similar propensity scores. Specifically, PSM estimates the average impact of program participation on participants by constructing a statistical comparison group on the basis of the probability of participating in the treatment T conditional on observed characteristics X, given by the propensity score: $P(X)=Pr(T=1/X)$ (Rosenbaum andRubin 1983; Abadie and 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 and 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 and 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 program participation (Heckman et al.1998; Bryson et al. 2002; Austin 2011).

The approach operates with the following two assumptions:

$$E(Y_0 \mid X, T=1) = E(Y_0 \mid X, T=0), \text{ and} \quad (7)$$

$$0 < P(X) < 1 \quad (8)$$

The first assumption (equation 7) 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 program. The second assumption (equation 8) is the assumption of 'common support' given by expression (7)[8]. 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 program, its targeting criteria, and previous theoretical and empirical studies. In this study, we 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).

The analysis presented in this paper fulfils the conditional independence assumption by including variables in the probit model that cover the eligibility criteria for the program but which cannot be directly affected by program participation (see **Table 1**). Moreover, in order to control certain community and district level characteristics that might affect program 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 program participation. These variables reflect that on average participants of the program seem to have low human capital as compared to non-participants. Climate shocks (that include an aggregate index of drought, flooding, and frost) have a positive and highly significant coefficient. As expected, such exposure to such shock is a primary factor for targeting households in the program. 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

[8]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).

negative and significant coefficients as compared to the reference region, Oromya. Tigray region shows a positive and significant coefficient.[9]

Table 1. Probit Estimations of major variables used in the PSM

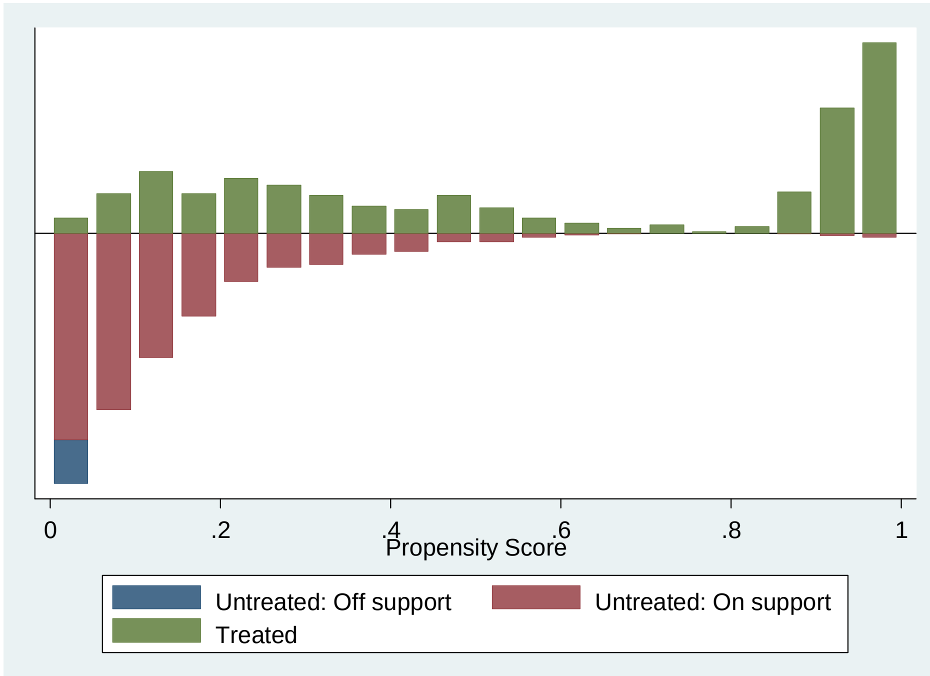
Age of household head	-0.06 (-0.03)
Male head (=1)	-0.756^{*} (-0.31)
Education of household head	-0.035^{*}(-0.02)
Dependency ratio	-0.18(-0.19)
Household size	-0.13(-0.11)
Livestock holding (tlu)	-0.01(-0.03)
Number of oxen	-0.12(-0.06)
Loan taken dummy (credit)	0.17(-0.09)
Participation in Iddir dummy (=1)	0.62^{***}(0.19)
Land size (in ha)	-0.41^{*}(-0.16)
Climate shock index	0.46^{***}(-0.09)
Ln crop income	-0.04 (-0.03)
_cons	-2.19 (-1.68)
N	1888
chi^2	841.40

Standard errors in parentheses
$^{*}p< 0.05$, $^{**}p< 0.01$, ***
Source: computed from ERHS 2004–2009.

The assumption of common support is also fulfilled by dropping 207 households whose propensity scores lie 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 2**. All results presented are based on specifications that passed the balancing tests. The propensity score is used here to match participant and

[9] 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.

control groups in the pre-program year (baseline) i.e. 2004 which is then used to estimate the DID.



Source: computed from ERHS, 2004–2009

Figure 2. Propensity score distribution among treatment and comparison observations

Results and Discussion

Vulnerability to climate-induced shocks

This paper attempted to determine the vulnerability of smallholder households to climate-induced shocks caused mainly by drought and floods using a comprehensive index–LVI. The LVI indicates that for all households, the mean LVI is 0.37. **Table 2** provides the three components of the LVI in terms of exposure, sensitivity, and adaptive capacity. Accordingly, the major contributing factor to the vulnerability of households is found to be exposure with a mean index value of 0.45, followed by the lack of adaptive capacity with a mean index value of 0.40 out of 1.

Table 2. Components of livelihood vulnerability index (LVI)

Variable	Mean	Std.Dev	Min	Max
Exposure	0.45	0.19	0.33	1.00
Sensitivity	0.35	0.20	0.03	1.00
Adaptive capacity	0.40	0.09	0.08	0.70
LVI_	0.37	0.09	0.12	0.67

Source: Author's computation from ERHS 2004-2009

Thus, most households (62.85 %) are highly exposed to climate-induced shocks and are equally more sensitive to the shocks. Looking at the extent of vulnerability by regions, the Southern Nations, Nationalities and Peoples Region (SNNPR) shows a relatively higher mean LRI (0.39) followed by Oromia and Amhara regions. In terms of PSNP status, the non-beneficiaries show slightly higher means LRI than beneficiaries in all regions except Tigray (see **Table 3**). This difference between beneficiaries and non-beneficiaries of the program is statistically significant at less than 1% as demonstrated by two-sample t-test result. Thus, participating in the PSNP is likely to reduce vulnerability by up to 0.038 points as compared to non-participation ($t=7.23$, $Pr(T > t) = 0.0000$). This result provides an initial evidence that PSNP may help to decrease the vulnerability of households to climate-induced shocks.

Table 3. Mean LRI (vulnerability) by PSNP status and region

PSNP	Tigray	Amhara	Oromya	SNNPR
Non-beneficiaries	0.29	0.36	0.38	0.41
Beneficiaries	0.32	0.35	0.35	0.38
Total	0.29	0.33	0.34	0.39

Source: Author's computation from ERHS 2004-2009

Impact of PSNP on Diversification

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. 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, the sale of animal products, and 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 program intervention. Moreover, income earned from renting land and oxen (rent income) as well as remittances are categorized as non-farm income.

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 4**). Off-farm income is likely to be significantly reduced by the program (up to 76 %) (Column 4, **Table 4**), 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	0.2721	-0.3142	-1.455
	0.0466	0.9000	0.0395	-0.0602
R.Sq	0.1272	0.0988	0.5313	0.2030
N	2072	1424	2037	312

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

Source: Author’s computation from ERHS dataset 2004-2009

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.

The DID analysis was further extended 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 5**).

Table 5. 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	0.1060	-2.2682
	0.1021	0.7988	0.9143
R.sq	0.4488	0.0026	0.0114
No. groups	1092	969	252

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

Source: Author's computation from ERHS dataset 2004-200

Since the focus of this paper is on non-farm income, a regression model with the two major components of non-farm income was performed to gain more nuanced insight into the influence of the program 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. This result seems to suggest that program 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 the schema that argues that 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.

The result on farm income has a negative sign and 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.[10] The lack of increased farm income shown in this analysis partly could be explained by the demand for household labour in public works reducing availability for farm activities, a crowding-out effect (Andersson et al.

[10]Devereux et al. (2006) states 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).

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, FedisKalu, 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 this analysis at least for own-business income, which has shown an increase due to program participation. This could suggest that the crowding out effect is seasonal in nature and seems to affect only farm activities.

Following Villa (2012)the DID was combined 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 6** and **7**. 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 andIchino2002; 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 and 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 6** 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 6. 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
Source: Source: Author's computation from ERHS dataset 2004-2009

Table 7 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 and 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 program'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 program, annual farm income on average is likely to decrease by up to 775.6 ETB (160 USD).[11] This substantial decline in farm income could lend support to the crowding-out effect of the PSNP previously discussed.[12]

As for non-farm income, we observe statistically significant and consistently increasing effects of program 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.

[11]The average exchange rate in 1994 was 1 USD-United States [US dollar / $] =4.84 ETB-Ethiopia [Ethiopian birr]
[12] Given that farm income distribution is right-skewed, the median might be more suitable measure than the mean.

Table 7. 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
$^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$
N.B. Outcome variables are estimated at levels without log transformations and the currency is given in ETB at 1994 prices.
Source: Author's computation from ERHS dataset 2004-2009

Off-farm income quintile estimations show interesting patterns in which program 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 program's effect on off-farm activities and income. Accordingly, for those who are already earning relatively higher income from off-farm activities, program 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 seems to suggest that PSNP may encourage negative forms of adaptation strategies. Since this assertion has important implications for the program'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, the same Kernel propensity score matched quintile DID was performed on income earned from the sale/extraction of natural resources component. The results are reported in **Table 8**. These results indicate that much of the increase in off-farm income is attributable to the 'temporary agricultural labour' 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 program 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 program's impact on off-farm income components.

Table 8. Kernel Propensity Score Matching Quintile DIDs for off-farm income categories

Agricultural labor	**ATT**	**Sale of natural resources**	**ATT**
Quintile 1	2.318(0.02)	Quintile 1	-104.7(-1.35)
Quintile 2	135.8***(2.69)	Quintile 2	-129.3***(5.91)
Quintile 3	181.17***(2.80)	Quintile 3	-268.1***(-16.27)
Quintile 4	179.74**(2.35)	Quintile 4	-290.8***(-171.9)
Quintile 5	586.2***(7.68)	Quintile 5	-231.4***(-7.86)
Quintile 6	565.13***(8.23)	Quintile 6	-308.1***(-8.72)
Quintile 7	344.58***(3.19)	Quintile 7	-196.91***(-2.88)
Quintile 8	1370.03***(5.68)	Quintile 8	-127.10(-0.86)
Quintile 9	1251.58(1.20)	Quintile 9	64.84(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: Computed from ERHS 2004–2009

In sum, the major result of the analysis is the consistent and robust positive coefficients of non-farm income across all estimations.[13] 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 program 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.

[13] 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.

Conclusions and Policy Implications

Following the 'adaptive social protection' framework discussed by Davies et al. (2013), and using a nationally representative dataset, this paper examined the role of social protection in reducing vulnerability to climate shocks and estimate the impact of PSNP on autonomous adaptation strategies. The results from the vulnerability analysis indicate that exposure and lack of adaptive capacity to climate-induced shocks largely explain the vulnerability of rural households to climate-induced shocks. Moreover, participating in the PSNP is likely to help to decrease this vulnerability. The results from the non-experimental estimations also indicate that receiving transfers from the PSNP, on average increases income from non-farm activities. These results confirm the hypothesis that social protection can promote positive adaptation strategies and may serve as an effective means of reducing the vulnerability of smallholders to climate change-induced shocks. Based on these results, it can be further argued that the PSNP as a major social protection scheme in Ethiopia can be integrated with climate change responses at various levels. Thus, the PSNP can contribute to climate change adaptation in a more sustainable manner if it adopts a long-term perspective that takes into account the increasing vulnerability to climatic shocks.

Supporting climate adaptation in social protection schemes requires more positive forms of income diversification than has been presented in this paper. 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.[14]

As shown in this paper, program 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 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

[14]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).

sustainable adaptive capacity requires reinforcing the farming sector.[15]Thus, although this has not been the topic of interest in this paper, the PSNP needs 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.

[15] 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).

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