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# Empirical Analyses on the Economics of Production: Employment, Productivity and Risk Management

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## Content

## Zusammenfassung

In den letzten Jahrzehnten war die Landwirtschaft verschiedensten Herausforderungen ausgesetzt. Um diesen Herausforderungen zu begegnen, unterliegen die Landwirtschaft wie auch der gesamte Lebensmittelsektor einem stetigen sozialen, strukturellen und wirtschaftlichen Wandel. Deshalb ist das Verständnis über die Ökonomie der landwirtschaftlichen Produktion mit ihrem dynamischen natürlichen, sozialen und politischen Umfeld ein wichtiges Diskussionsthema und ein Schlüsselanliegen der Entwicklungspolitik. Diese Dissertation präsentiert empirische Untersuchungen zur Ökonomie der landwirtschaftlichen Produktion mit Fokus auf Beschäftigung und Arbeitsbedingungen, Klimawandel und Risikomanagement, Produktivität und Wohlfahrt landwirtschaftlicher Betriebe.

## Summary

In the last couple of decades, agriculture has faced a number of critical challenges. To cope with these challenges, agriculture and the food sector have gone through continuous social, structural and livelihood transitions. Understanding the economics of agricultural production with the dynamic natural, social and policy environment is an important topic for discussion and key concern for development policy. This dissertation presents empirical investigations on the economics of production in agriculture by giving particular emphasis to employment and labor conditions, climate change and risk management, productivity and welfare of farms.

# 1. Introduction

In the last couple of decades, farms in both the developing and the developed world have gone through different historic structural, economic and livelihood transitions (Chaplin et al., 2004; Christiaensen et al., 2011; European Commission, 2013). Continuous technological progress, shifts in the political economy in the world, institutional and organizational transformations, climate variabilities, population growth, human capital and resource endowment changes substantially contribute to these transitions (Godfray et al., 2010; Jayne et al., 2010; Jongeneel et al., 2008; Masanjala, 2006). The role of agriculture for employment, export earnings and the overall economy substantially varies between the developing and developed world (Christiaensen et al., 2011; Eurostat, 2013; Jayne et al., 2003).

There is no clear universal trend in the transition process. In some parts of the world, farms grew bigger in size and made substantial changes in the scale of mechanization (Bartolini and Viaggi, 2013; Deininger and Byerlee, 2012; European Commission, 2013; Eurostat, 2013). Such a transition can be associated with the efficiency of the factor market (e.g. credit market, land market, labor market). During this process, a substantial proportion of farmers exit the sector (Breustedt and Glauben, 2007; Hazell, 2005; Kazukauskas et al., 2013; Meert et al., 2005). This demographic transition can be a response to increased productivity of the manufacturing sector, expected high quality of life as well as rural urban wage disparities (pull factor); and/or a push factor including pervasive effects of climate change.

On the other hand, land fragmentation and significantly decreasing average per capita farm size seem to be the case in most parts of Africa and Southeast Asia (Masters et al., 2013). In many countries, agriculture is the major livelihood activity for the people and the sector substantially contributes to the overall economy. In these countries, improving the production and productivity of smallholder farms play a substantial role for poverty alleviation. Accordingly, there is a continuous call to transform the institutional, organizational and policy environment so as to support smallholder farmers (Griffin et al., 2002; Larson et al., 2014; Poulton et al., 2006). However, there is a longstanding and an unsettled discussion on the relationship between productivity (efficiency) and scale with respect to small and large farms (Carter, 1984; Collier and Dercon, 2014; Fan and Chan-Kang, 2005; Woodhouse, 2010).

In some countries, specialization of agriculture has gained greater importance (Kurosaki, 2003; OECD, 2001). The gain from scale economies gives a stronger economic incentive for specialization in the farm. There are also factors that contribute to growth in specialization of farms including infrastructure development, commercialization of agriculture and export market trends (Latruffe et al., 2005; Mora and Moreno, 2010; Naudé et al., 2010; Paul and Nehring, 2005). On the other hand, there are arguments about the higher likelihood of depletion of resources associated with specialized agriculture. Economies of scope and agricultural risk can explain part of the diversification puzzle. As a response, farms in some parts of the world exhibit greater diversification and multi-functionality (Di Falco and Chavas, 2006; Havlík et al., 2005; Jongeneel et al., 2008; Kandulu et al., 2012). These transitions towards specialization or diversification affect resource allocation decisions and consequently result in welfare gains (or losses).

There is a growing population in sub-Saharan Africa (SSA) despite continuously shrinking farm size, limited progress in technological development, low level of adoption of improved technologies, underdeveloped infrastructure and limited agribusiness innovations (Holden and Otsuka, 2014; Thirtle et al., 2003). These transitions cause growing landlessness for the rural population, and limited employment possibilities for the youth (Bezu and Holden, 2014; Teklu and Asefa, 1999). In addition, the slower rate of growth in urbanization and poor performance of the manufacturing sector provide limited pull factors in SSA (Anyanwu, 2013; Bryceson, 2002; Tiffen, 2003). In addition, the rural youth is often less educated, unskilled, and unfit for many skilled urban jobs. As labor is one of (perhaps the major) resource that smallholders rely on to meet their livelihood requirements, growing unemployment is among the key development challenges in SSA. These therefore require policies and strategies to promote employment opportunities and to improve the quality of the existing ones (FAO, 2010, 2012, 2014).

Considering the quality of work as a key element of life and production, the International Labor Organization (ILO) developed a “Decent work agenda” (Somavia and General, 1999). In the last two decades, the decent work concept has been further adapted to agriculture and promoted by the FAO (FAO, 2010, 2012, 2014). Better working environments, health and safety conditions, abolition of child labor, gender equality, adequate provision of social protection and promotion of social dialogue with better pay and living conditions are expected to improve worker performance and productivity (Basu and Tzannatos, 2003; Bloom et al., 2009; Bloom and Van Reenen, 2006; Golden, 2011). Nonetheless, empirical literature that documents the role of decent rural employment on agricultural productivity, poverty and livelihood is rather rare for the developing world. The majority of the poor in the developing world live in rural areas and their livelihood predominantly depend on agriculture. As most of the poor relay on agriculture as a means of livelihood, promoting the (quantity and quality of) employment and labor productivity has more relevance in regard to poverty reduction.

Climate change is one of the key factors that might shape the transition of agriculture and rural livelihood (Battisti and Naylor, 2009; Eakin, 2005; Hardaker et al., 2004; Intergovernmental Panel on Climate Change, 2007). The implications of climate change vary across regions. A small projected increase in temperature could lead to small productivity gain in agricultural production in some parts of the temperate zone (Intergovernmental Panel on Climate Change, 2007; Olesen and Bindi, 2002). On the other hand, such a projected increase in temperature is expected to have detrimental effect for agricultural production in the tropics and subtropics (Barrios et al., 2008; Dinar et al., 2012; Intergovernmental Panel on Climate Change, 2007; Rowhani et al., 2011). In some parts of the Sahel and sub-Saharan Africa, drought caused disastrous consequences for the livelihood of the poor (Dercon and Krishnan, 2000; Morrissey, 2013; Morton, 2007).

Climate change impacts on farm production, income and livelihood can be determined by a number of associated factors. The frequency of the occurrence of these events (drought, flood, hail, seasonality of rain, hurricanes etc.), the severity of the event, and adaptation capacity (of individuals, farms, communities, etc.) play crucial role (Di Falco, 2014; Dinar et al., 2012; Hardaker et al., 2004; Intergovernmental Panel on Climate Change, 2007). In this regard, improving the adaptive capacities of farmers is an important area of research and development.

In order to mitigate the negative impacts of climate change in agriculture and livelihood, farmers may adopt a range of risk management options (Dinar et al., 2012; Hardaker et al., 2004; Kandulu et al., 2012). Livelihood diversification is among the key risk mitigation instruments that are widely employed both in the developing and the developed world (Barrett et al., 2001; Bezabih and Sarr, 2012; Di Falco and Chavas, 2006; Finger and Buchmann, 2015). The role of farm (enterprise) diversification is especially crucial in countries where other forms of risk management instruments (e.g. insurance, contracts and futures, irrigation etc.) are not well-developed (Barrett et al., 2001; Chavas and Di Falco, 2012). In addition to the risk mitigation role of farm diversification, productivity gains from scope economies with complementarity between production activities may encourage farm diversification (Chavas and Di Falco, 2012; Kim et al., 2012; Paul and Nehring, 2005).

Recent studies highlight the impact of social capital on the adoption of risk management activities (Di Falco and Bulte, 2013; Wossen et al., 2015). Di Falco and Bulte (2013) for instance highlight that compulsory risk sharing discourage the adoption of climate risk management activities (in this case, soil and water management schemes). This indicates that farmers may use their social networks and informal institutions as a safety net to provide a buffer against shocks. Similarly, Paul et al. (2016) analyze the role of social capital (measured as trust) on the adoption of individual and community based risk mitigation strategies. They documented that greater social capital promotes community based adaptation, while discourages individual based adaptation to climate change. These empirical findings indicate that there could be substitution between household climate change risk mitigation instruments (for example enterprise diversification) and social capital. However, economic theories highlight that complete substitution of other risk mitigation instruments with social capital for covariate risks (such as climate shocks) can be sub-optimal and disastrous.

Farms can also employ market based risk mitigation instruments. Insurance is among the widely discussed and employed market based risk mitigation tools in agriculture. The insurance market has a long history in some parts of the world (Enjolras and Kast, 2012; Enjolras and Sentis, 2011; OECD, 2009). There are efforts to promote the insurance market in the developing world. Willingness to pay for insurance is often determined by the expected probability and cost of risk, previous experiences and the trade-offs and complementarities with other risk management instruments. For instance, Enjolras and Sentis (2011) using data from France show that farmers with previous insurance claims have higher propensity of purchasing insurance policies. This indicates the positive learning effect of a well-functioning insurance market to encourage farmers to engage in the insurance market. Nonetheless, there are also stories that show unintended consequences of highly subsidized public insurance schemes that aim to introduce and promote insurance markets in the developing world. According to Duru (2016), farmers with pre-existing public safety net experiences fail to take up newly introduced private index insurance schemes. According to Di Falco and Bulte (2013), those with strong social networks are less likely to adopt soil and water conservation schemes for risk mitigation. These empirical works raise an empirical question on the possible interdependence (e.g. complementarity, substitution) between risk mitigation instruments.

Overall, the environment is increasingly dynamic, and agriculture has gone through continuous social, structural and livelihood changes. These transitions exhibit different pathways across countries and regions. In this regard, understanding the economics of agricultural production with the dynamic natural, social and policy environment is an important topic for discussion and a key concern for development policy. This dissertation presents empirical evidences on the economic implications of labor and decent employment, farm diversification, social capital and adaptations to climate change using datasets from different countries.

The next chapter illustrates and discusses the conceptual approach and empirical framework employed in the dissertation. The empirical strategy in this dissertation is based on the classical utility maximization framework. In this particular setting, the empirical analyses presented in this dissertation assume that farm households make their decisions (e.g. adopt technologies, participate in certain programs, allocate resources etc.) in order to maximize utility given a set of constraints.

Chapter 3 presents a paper on the relationship between decent rural employment and agricultural production efficiency. The analysis is based on a multi-output distance function framework using cross-sectional data from Tanzania and Ethiopia. Based on the available data and specific local conditions in the two countries, we develop indicators of decent rural employment. It follows the definitions and pillars of the decent rural employment concept developed by ILO and FAO (FAO, 2010; Somavia and General, 1999). The indicators of decent rural employment that are used in the analysis include employment creation (employment to work force ratio), standards and rights at work (precarious employment ratio and child labor ratio in the household), and social protection provision (share of government transfer from income of the household) in the two countries. The analysis shows that decent rural employment is significantly associated with agricultural production efficiency in the two countries. Whereas higher employment to work force ratio and increase in social transfers improve production efficiency, higher precarious employment ratio and child employment ratio reduce production efficiency.

In chapter 4, the empirical relationship between the cost of risk exposure and income diversification is investigated. We employ a profit moment approach (Antle, 1983, 1987) to estimate the risk premium, and then estimate its effect on the income diversification of the household. Ethiopia experienced a couple of shocks in the last decades, and some of them have disastrous livelihood, social and political consequences for the country. This provides us a situation to evaluate the implications of risk. For the specific analysis, we use panel data from 2004 and 2009. The empirical analysis shows that risk exposure constitutes a significant proportion of the farm income. The analysis also demonstrates that risk premium explains part of the income diversification puzzle. This implies that farmers that experience a higher cost of risk are likely to move towards diversifying their income sources, and that a lower cost of risk promotes specialization.

Chapter 5 presents an empirical analysis of the interdependence between social capital and enterprise diversification using panel data from Ethiopia. The role of social capital for risk management is evident in the case of idiosyncratic risk (risk that is unique to the individual) where a shock is less likely to affect all the members of the network. The empirical question here is to evaluate whether social capital can be helpful for management of covariate risks (risk that affect network members in the same way). The empirical analysis further explores the relationship across regions with differences in climate change effects. For this particular case, indicators for the defensive dimensions of social capital ("if the household head believes he can borrow at hard times" and "whether the household has at least one group-based funeral insurance scheme locally called – *iddir*". The result confirms that social capital is significantly associated with income diversification, implying that smallholder farmers can use social capital as a risk management strategy. The analysis also verifies that the effect of social capital on income diversification is weaker in regions that are more prone to climate change. This demonstrates that, to a certain extent, farmers have understood that social capital might not be an effective tool against non-idiosyncratic risks including climate shocks.

In chapter 6, the relationship between risk exposure, climate variabilities, adaptation and investment is examined. The study further investigates the interdependence between risk management strategies (farm diversification and purchase of insurance policies) and farm investment decisions. For this study, we use the Farm Accountancy Data network (FADN) panel data (1989-2009) of German arable farms together with weather data. The results confirm that higher variance of profit and downside risk are associated with farm diversification and purchase of insurance policies. Conversely, higher variance and higher downside risk discourage farm investment. The empirical study also demonstrates that farm diversification, purchase of insurance policies and investment decisions are interdependent.

Chapter 7 presents an empirical evidence on the productivity and risk management implications of farm diversification. Using the certainty equivalent approach, the effect of farm diversification on productivity and reduction of the cost of risk are studied. For the empirical investigation, we employ panel data from 1989-2009 for Germany. Using a stochastic production frontier approach, the empirical study compares the welfare (through productivity and risk premium) of diversified and specialized farms. The welfare of farms is examined across different diversification scenarios developed by changing the crop mix. This empirical analysis illustrates that farm diversification is associated with farm productivity and it contributes to the reduction of the cost of risk. The study also demonstrates that the gain from farm diversification substantially varies with the diversification scenario. Furthermore, the analysis shows that the gain from diversification depends on the complementary, scale and concavity incentive (disincentive) from the combination of farm activities in the farm portfolio.

The last chapter provides conclusions, discusses policy implications of the findings and suggest areas of future research. Table 1 summarizes the individual chapters and their contributions.

Table 1. Contributions of individual chapters

| Topic | Hypothesis | Contribution |
|---|---|---|
| **Chapter 3**: Decent rural employment | Decent rural employment improves agricultural production efficiency | Existing empirical papers focus on the manufacturing and service sectors. This study provides an empirical evaluation of the role of decent employment in agriculture. |
| **Chapter 4**: Cost of risk and income diversification | Farmers that experience external shocks and higher cost of risk are likely to diversify more | To the best of authors' knowledge, this is the first study that investigates the relationship between exposure to risk (measured with risk premium) and income diversification decisions. |
| **Chapter 5**: Risk exposure, adaptation and investment | Farmers with higher cost of risk do diversify more, pay for more insurance and reduce investment | This is the first study that simultaneously analyzed the effects of risk exposure on diversification, insurance and investment decisions together. In this approach, the interdependence between diversification, insurance and investment is investigated. |
| **Chapter 6**: Social capital, climate change and income diversification | Social capital is related to diversification, and the effect varies with variations on climate change effects | There are efforts that documented the role of social capital for risk mitigation. This is the first study that assess the interdependence between social capital and income diversification with respect to variations on climate change effects. |
| **Chapter 7**: Welfare implications of farm diversification | Diversified farms are different with respect to productivity, risk premium and welfare compared to specialized farms. | Whereas there are papers that analyze the role of risk mitigation by farm diversification, and the productivity impacts of specialized farms, there is no comprehensive study that analyze the welfare implication of diversified farming, and across different diversification scenarios. |

## 2. Conceptual and empirical approach

In order to analyze and quantify the relationship between resource allocation decisions, productivity and risk in agriculture in an uncertain environment, we first define the conceptual and empirical framework. The conceptual and empirical frameworks are vital to provide a base for defining the nature of relationships, their interpretations and policy implications. The aim is to analyze the relationship between resource allocation decisions in agriculture and some performance and welfare dimensions (productivity, efficiency, risk management). Depending on the resource endowments, available opportunities and their choices, rural households can engage in one or multiple production activities. The input and resource transformation process with respect to outputs, and further to welfare of the household in an uncertain environment is illustrated by Figure 1.

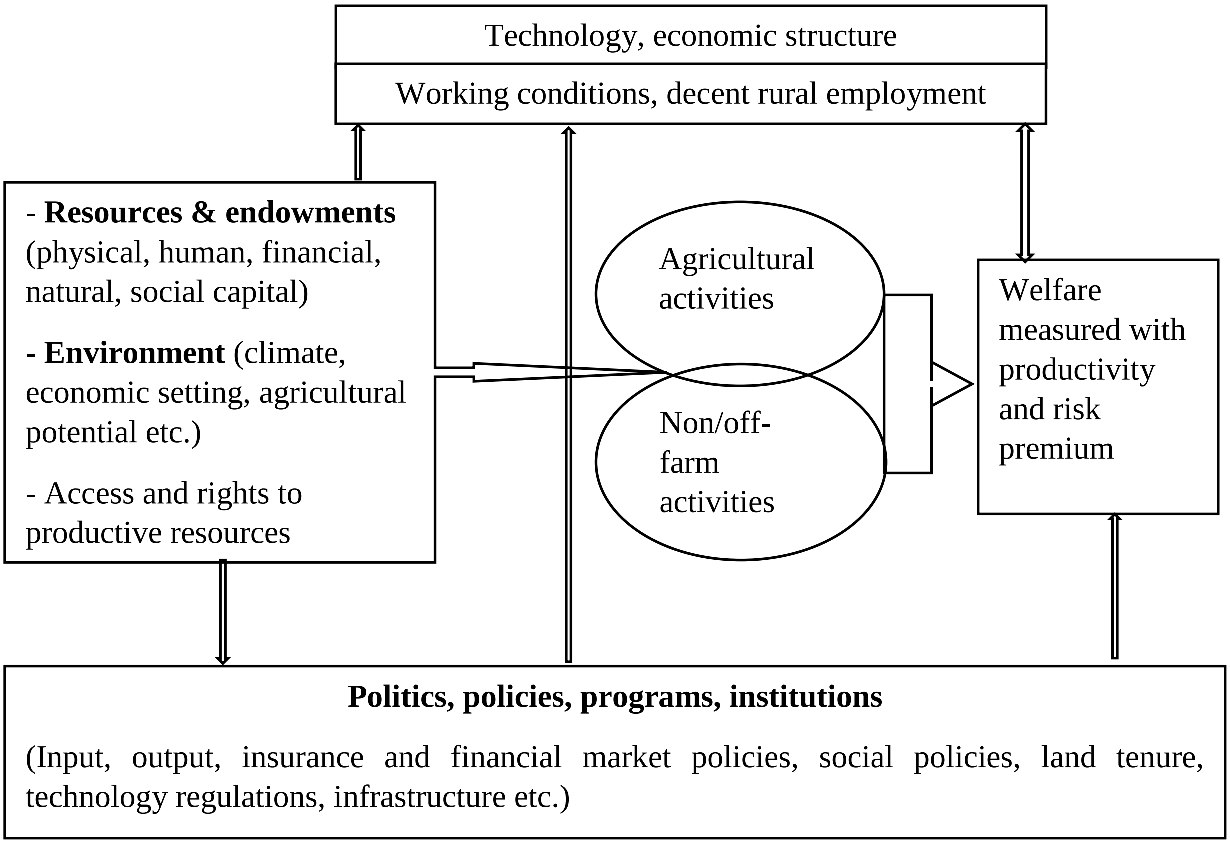


Figure 1: Conceptual framework for resource allocation, productivity and risk. Adapted from Pender et al. (2006).

In a utility maximization framework, a farmer makes decisions to employ productive resources in order to maximize the utility from these production activities. In this framework, it is possible to evaluate the economic performance of production activities using direct or indirect welfare measures (e.g. productivity and risk management). The underlying policy in the country (or region, world) can shape the economic structure and productivity, technology development and transfer process, employment and working conditions. These all are likely to influence the performance of production activities and welfare.

Production environment and climate play a substantial role in this process, and agriculture is one of the most exposed sectors to changes in climate (Dinar et al., 2012; Intergovernmental Panel on Climate Change, 2007). As a response, farmers use strategies that can reduce the exposure to risk, or improve the resilience capacity to the exposure to risk. The risk management instruments can be classified into ex-ante and ex-post measures. Examples of such risk management strategies include farm diversification, off-farm activities, formal and informal insurance schemes, etc. Farmers that are exposed to risk also look for risk coping strategies that include sale of livestock and other valuable assets, reduction of investment and consumption etc.

In the process of changing productive resources in to goods and services, working conditions and the working environment can contribute to improve/hinder performance (Ghai, 2002). The quality of work, defined as decent rural employment by ILO and the FAO, consists of the creation of productive employment (e.g. employment rate, adequate income generation aspects, pay rates etc.), standards and rights at work (e.g. precarious employment, child labor, forced labor, discrimination etc.), social protection (e.g. occupational safety and health, social protection coverage, working conditions etc.), and governance and social dialogue (e.g. labor unions, representations) (FAO, 2010; Somavia and General, 1999). A crucial step here is to find indicators from the above mentioned set of dimensions of decent employment.

A conceptual framework is constructed to represent the transformation of resource endowments (physical, human, financial, natural and social capital) in to welfare dimensions in an uncertain environment. Throughout this transformation process, available technologies in the production system, economic structure and conditions, formal and informal institutions, policies and the political environment etc. can play vital role (Figure 1).

Consider a farmer with limited resources, and who would like to engage in production activities. Following an input-output transformation notation based on a utility maximization framework, a farmer is assumed to maximize expected utility of profit $EU(\pi)$ that can be gained from the chosen production activities given her/his resource constraints. The underlying condition in a farm context assumes a rational farmer that makes production decisions in order to maximize her/his utility in the feasible production set based on her/his resource constraints.

A utility maximization framework of a farmer can be reduced in to maximization of the certainty equivalent ($CE$) of the farm from production activities. Certainty equivalent (CE) is a welfare measure defined as the sure payoff of production activities satisfying:

$$EU(\pi) = U(CE) \tag{1}$$

where $E(U(\pi))$ is the expected value of the utility of profit of the farm operator. $U(\pi)$ is a strictly increasing stochastic function, and has very important implications for welfare and risk analysis. We will briefly discuss the interpretation of the utility of profit related to risk perceptions by the decision maker later in this chapter. A farmer allocates inputs (land, labor, capital etc.), and these are represented with an input vector $(x)$. These inputs are employed to produce output vectors $y$ (crop, livestock products etc.). This relationship can be represented through an input-output transformation technological set. Following the specification introduced by Farell (1957), this input-output transformation function can be specified as:

$$\text{S} = \{(x, y): x\ produces\ y\} \tag{2}$$

Where *S* is a representation of the production technology with a feasible set, using input vector x= $(x_1, x_2, \dots, x_n)$ to produce output vector y= $(y_1, y_2, \dots, y_m)$.

We can re-write the multi-output production function presented in (2) using a stochastic distance function framework. In a parametric setting with more than one output, an input oriented or output oriented Stochastic Distance Function (SDF) can be used. Under perfect market condition, both an input oriented or output-oriented SDF approach should provide the same result. Output[1] oriented distance function can be mathematically represented as:

$$d_i^o = d^o(x_{1i}, x_{2i} \dots x_{Ni,} y_{1i,} y_{2i} \dots y_{Mi}) \tag{3}$$

Equation (3) describes an output oriented distance function as a technological set of producing M number of positive outputs $(y = y_1, y_2, \dots, y_M)$ using N number of non-negative inputs $(x = x_1, x_2, \dots, x_N)$.

[1] The detailed illustration of why we choose output oriented distance function can be found in chapter 3.

By choosing one of the outputs as a reference point (i.e. $y_{Mi}$ be the dependent variable), and by replacing the distance parameter with the error term, it can be observed that this coincides with the classic stochastic frontier specification of the input-output relationship.

$$-\ln y_{Mi} = ln\mathrm{f}\left({}^{y}/_{y_M}, \mathrm{x}, \beta\right) + \ v_i + u_i \tag{4}$$

Where β is a vector of technological coefficients associated with each inputs and outputs in the technological frontier and i is an index for households. The error term in (4) is composed of the noise component $v_i$ and the inefficiency parameter $u_i$.

In general, such multi-output and input relationship can be written in a production function as follows.

$$y_1 = f_1(y_2, \dots, y_m, x, \beta) + e \tag{5}$$

In this multi-output and multi-input stochastic specification, $e$ is the stochastic error term. This stochastic input output relationship can be extended to accommodate risk analysis, through the probability distribution of shocks.

Back to equation (1), the certainty equivalent is derived from a productivity-risk framework allowing for the inclusion of the farmer's risk preferences. Under decisions $z$, the certainty equivalent can be written as (Pratt, 1964)

$$CE(z)_i = E(\pi(z)_i) - R(z)_i \tag{6}$$

where $R(z)$ is the risk premium. This representation shows that the decision $z$ has an important role to determine both the expected value of profit and the risk premium of the household. In this dissertation, the decision could be input and output decisions, employment and decent work, farm and non-farm diversification activities, purchase of insurance policies, social capital and investment and disinvestment decisions. These decisions are made on the farm relative to their expected welfare.

For a given $z$, the risk premium $R(z)$ is the sure amount of money that a farmer is willing to give up to eliminate risk exposure (Arrow, 1965; Pratt, 1964). This is an implicit cost of risk which can be interpreted as the willingness to pay for risk management options and strategies. An example is the willingness to pay for insurance. In general, the risk premium $(z)$ depends on the farmer's risk preferences, where a positive $(z)$>0 implies the farmer is risk averse.

Equation (5) captures the expected input and output relationships in the presence of production risk, and provides an analytical approach to reach to expected value of profit and risk premium introduced in equation (6). Using a moment-based approach (Antle, 1983, 1987), one can evaluate the economic value of risk. The error term that we can get by rearranging equation 3, $u = y_1 - f_1(y_2, \dots, y_m, x, \beta)$ reflects production risk. The second moment function (i.e. variance) and third moment function (i.e. skewness) are represented as follows:

$$E(u)^2 = Var(\pi) = h_2(y_2, \dots, y_m, x, \beta_2) \tag{7a}$$

$$E(u)^3 = Skew(\pi) = h_3(y_2, \dots, y_m, x, \beta_3) \tag{7b}$$

Under Constant Relative Risk Aversion (CRRA), where the risk aversion measure is assumed to be the same irrespective of the level of wealth, the risk premium $R(z)$ can be written as a function of the moments of the payoff distribution as:

$$R(z) = \frac{\alpha}{2} \frac{Var(\pi)}{E(\pi)} - \frac{\alpha(\alpha+1)}{6} \frac{Skew(\pi)}{[E(\pi)]^2} \tag{8}$$

Finally, the utility maximization framework introduced in (1), and the follow-up conceptual models on productivity and risk (equation 2 – equation 8), help us to analyze the economics of agricultural production. Specifically, we employ the multi-output SDF to investigate the relationship between decent rural employment and agricultural production efficiency presented on Chapter 3. The certainty equivalent framework presented in (6) is key to analyze the calculation of profit moments (first, second and third), and their implications on farm diversification, purchase of insurance and investment (Chapters 4 and Chapter 6). Similarly, the analysis employs the certainty equivalent framework for estimating the welfare implications of farm diversification (Chapter 7).

# 3. Decent rural employment and agricultural efficiency: Empirical evidence from Tanzania and Ethiopia

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**Abstract**

Promoting decent rural employment, by creating new jobs in rural areas and upgrading the existing ones, could be one of the most efficient pathways to reduce rural poverty. This paper systematically investigates the impact of decent rural employment on agricultural production efficiency in Ethiopia and Tanzania. The analysis applies an output-oriented distance function approach with an estimation procedure that accounts for different technological, demographic, socio-economic, institutional and decent rural employment indicators. Data of the most recent round of Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for the two countries are used, and a set of indicators is derived to proxy core dimensions of decent rural employment. The findings of our analysis show that decent rural employment contributes to agricultural production efficiency.

**Keywords:** decent work, rural employment, distance function, efficiency, poverty reduction

**JEL classifications:** D13, D24, J08, J24, J28

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## I. Introduction

Unfolding the complex relationship between employment, labor supply, factor markets and productivity is a crucial aspect in development research and policy design (Barrett et al., 2008; Rao et al., 2005; Satch and Temple, 2008; Todaro and Smith, 2012). Uncertainties regarding the interdependence of economic and population growth, sustainability, labor, poverty, as well as working and living conditions generated a great deal of discussions for decades (Harris and

Todaro, 1970; Ortega and Marchante, 2010; Satch and Temple, 2008). Policies around the employment-economic growth nexus emphasize the importance of the quality of employment and working conditions, as coined by the very concept of decent work and its policy agenda. With the aim of capturing diverse aspects of quality of employment, ILO developed the "Decent Work Agenda" (Somavia and General, 1999).

A number of empirical works highlight the implication of rural farm and non-farm employment for income growth and livelihood improvement. By providing access to income, rural farm and non-farm employment are crucial for ensuring food access (FAO, 2012; Haggblade et al., 2010; Lanjouw and Murgai, 2009). This is even more crucial for the poor and landless, as their labor is often the main asset that they can rely upon for income generation. On the other hand, Reardon et al. (2000) and Lanjouw and Lanjouw (2001) question the conventional wisdom on the contribution of the non-farm sector. They indicate that it is often inconclusive as there exist mixed findings in terms of labor productivity, income inequality and capital turnover in the rural non-farm sector (ibid). Furthermore, competition with respect to labor and other inputs from the non-farm sector might impede farm productivity.

There are some empirical works that attempt to specifically analyze the impact of some labor dimensions (for instance, tenure stability, flexibility and length of working hours, shared profit and management) on productivity of manufacturing firms and service provision (Bloom et al., 2009; Bloom and Van Reenen, 2006; Burchell et al., 2013; Ortega and Marchante, 2010; Vandenberg, 2004). Empirical works that analyze the effects found varied impacts across different industries and sectors, occupations and companies, worker demographics and performance of the economy (Basu and Tzannatos, 2003; Golden, 2011; Kelly and Moen, 2007). For instance, some empirical works indicate the role of "fair", "efficient" and higher wages, and flexible working time on the level of productivity and improvement of service provision (Akerlof and Yellen, 1990; Bloom et al., 2009; Bloom and Van Reenen, 2006; Katz, 1986; Mas, 2006). Others have concerns on the likely counter-productive impacts some dimensions of decent work (Basu and Tzannatos, 2003; Slater and Farrington, 2006; UNICEF, 1995). UNICEF (1995) and Basu and Tzannatos (2003) reported that attempts towards decent work in a poor economy, for instance by banning child labor or their products, might sometimes backfire and leave the family under starvation due to loss of income. Slater and Farrington (2006) also argue that social protection and cash transfer programs might sometimes reduce the motivation to look for alternative livelihood options.

Decent work literature on the developing world is rather thin and even more so when applied to agriculture and rural areas. And yet it is precisely in these contexts where the link between (quantity and quality of) employment and productivity has more relevance in regard to the effort to reduce poverty. Furthermore, it is precisely the rural poor who are often most exposed to pervasive decent work deficits, in terms of insecure and low incomes, poor health and safety conditions, child labor, gender inequality, inadequate social protection and lack of social dialogue (FAO, 2012, 2014). Decent rural employment, either in the agricultural wage employment or in the rural non-farm sector, is seen as a key component of integrated strategies to reduce rural poverty and enhance food security (FAO, 2010, 2012, 2014).

Various empirical studies were done on the sources of agricultural productivity and efficiency difference in the developing world, including sub-Saharan Africa and the developing world (Alene and Zeller, 2005; Anriquez and Daidone, 2010; Chavas et al., 2005; Solís et al., 2009). They report that poverty status, access to credit, land ownership and quality, human and social capital, labor sharing arrangements are likely to influence the level of efficiency of farms. Nonetheless, studies that explicitly analyze the implications of employment quality in and outside the farm on agricultural production efficiency are in an infant stage. This paper fills the existing shortfall in the literature, by shedding empirical light on the relationship between decent rural employment and agricultural production efficiency, taking Ethiopia and Tanzania as case studies.

## II. Conceptual framework

The ILO defines decent work as “a condition which promotes opportunities for work, freedom of choice, equal treatment, security of job, and dignity for both men and women” (Somavia and General, 1999). The term decent work is considered as one of the fundamental aspects of quality of life (Anker et al., 2003; Burchell et al., 2013; Somavia and General, 1999; Vandenberg, 2004). It comprises fair pay levels, safe working conditions, non-discrimination, job security and social protection, as well as satisfaction of the employee (Anker et al., 2003; Ghai, 2002). This also complies with core labor standards[2], provides sufficient income, reasonable working conditions, respect occupational safety and health standards, thereby empowering rural workers and their families to lead productive, healthy and dignified lives. With the aim of addressing all these dimensions, ILO developed the “Decent Work Agenda” with four core pillars: (i)

[2] Core labor standards include: freedom of association and effective recognition of the right to collective bargaining; the elimination of all forms of forced or compulsory labor; the effective abolition of child labor; and the elimination of discrimination in respect of employment and occupation.

employment creation and enterprise development, (ii) social protection, (iii) standards and rights at work, and (iv) social dialogue.

The multi-dimensional nature of decent work comes with many measurement challenges. These measurement challenges become particularly pungent when applying decent work to the specific features of the agricultural sector and the rural settings in developing countries. Ghai (2002) underscores that it is rare and impractical to find a unique and best indicator for decent employment, and an index of combinations of indicators could be a robust alternative. In the developing world, in addition to agricultural labor as the main source of livelihood, the rural non-farm sector absorbs a significant proportion of rural labor (Bezu and Holden, 2014; de Janvry and Sadoulet, 2001; World Bank, 2007). Hence, decent rural employment concept in the household should comprise both agricultural and non-agricultural employment, as well as self-employment and wage employment[3]. For this paper, we have identified indicators for three out of four pillars of the decent work agenda[4] that capture the core dimensions of decent rural employment.

Table 1: Decent rural employment indicators and expected relationship with efficiency

| Pillar of decent work | Indicators used | Measurement |
|---|---|---|
| Pillar1: Employment creation | Employment ratio* | Proportion of employed members to total workforce available in the household |
| Pillar 2: Social protection | Share of government transfer to income * | Proportion of government transfer to the total income of the household |
| Pillar 3: Standards and rights at work | Child labor ratio†[5] | Proportion of child labor from the total labor used for agriculture activities |
| | Precarious employment ratio* | Proportion of seasonal and casual labor from the total agricultural workforce |

Notes: * Ethiopia & Tanzania; † Tanzania

Under pillar one of decent work, we use the proportion of household members involved in productive work, either in terms of self-employment or in some kind of wage employment, to total household workforce[6]. For the social protection pillar, we employ receipt of cash and food

[3] Rural employment covers any activity, occupation, work, business or service performed by rural people, for remuneration, profit, in cash or in kind, including both agricultural and non-agricultural activities.
[4] Data at disposal do not allow for capturing indicators for the fourth pillar of decent work, on social dialogue, nor the other dimensions of decent rural employment (such as occupational health and safety).
[5] Child labor ratio as an indicator is used only for Tanzania due to low response rates in Ethiopia.
[6] We have built this indicator adapting the “employment-to-population” ratio to our analytical setting and data at disposal. Hence, employment-to-population ratio is the proportion of those who were employed over the last 7

transfers[7] in Tanzania; and transfers from the Productive Safety Net Programme (PSNP) for Ethiopia. The standards and rights to work pillar is proxied through two indicators capturing forms of employment deemed non-desirable or 'non-decent' in agriculture, namely child labor and precarious forms of work used for agriculture activities by a given household.

## III. Data and empirical model

### Data and summary statistics

Ethiopia and Tanzania are the case studies used to test the hypothesis. While the two countries are diverse in many ways, their agriculture sectors are deemed representative of many sub-Saharan African countries. Namely, rural realities where agriculture is the mainstay of the economy, and is predominantly composed of small-scale, subsistence-oriented farming activities as well as significantly dominated by crop-livestock mixed production systems. For the study, we have used cross-section data of the Living Standards Measurement study-Integrated Surveys on Agriculture (LSMS-ISA)[8] made available by the Development Research Group of the World Bank in 2011. The analysis is based on 1,151 and 931 observations in Ethiopia and Tanzania respectively.

Table 2: Descriptive statistics of the sample

| Variables | Ethiopia<br>Mean (Std. dev.) | Tanzania<br>Mean (Std. dev.) |
|---|---:|---:|
| Age of the Household head | 44.19 (14.20) | 47.58 (14.32) |
| Age dependency ratio | 1.25 (0.91) | 1.14 (0.82) |
| Family size | 5.66 (2.04) | 5.25 (3.12) |
| Sex of the household head (1=male, 2=female) | 1.12 (0.32) | 1.13 (0.34) |
| Household head literacy (1=literate, 2=Illiterate) | 1.58 (0.49) | 1.74 (0.56) |
| Annual precipitation | 942.39 (373.38) | 1061.16 (221.02) |
| Wettest quarter precipitation | 613.93 (240.51) | 570.45 (128.08) |
| Land in hectares | 1.21 (1.93) | 3.34 (5.19) |
| Intermediate inputs | 16.98 (27.15) | 5202.64 (12157) |
| Labor in days | 149.54 (171.98) | 189.49 (178.80) |

days reference period as self-employed, part-time, casual or seasonal work on farm/off/ or non-farm, after controlling for those who are inactive (went for schooling, ill and physically incapable).

[7] It is an aggregate measure of free food distribution, food, cash and input for work, scholarships or bursaries for primary or secondary school from the government or NGOs (in Tanzanian Shilling).

[8] The LSMS-ISA dataset is freely available for the public

| | | |
|---|---|---|
| Livestock in TLU | 5.82 (4.68) | 1.84 (6.56) |
| Capital expenditures | 24.50 (275.59) | 205458 (359716) |
| Concentration index (Herfindahl index) | .661 (.172) | .763 (.171) |
| Crop harvest in quantity index | 300.17 (542.82) | 513037 (1000000) |
| Livestock outputs in quantity index | 153.02 (751.48) | 205458 (359716) |
| Employment to workforce ratio | 0.80 (0.25) | 0.81 (0.26) |
| Share of government transfer to income | 0.98 (12.56) | 0.34 (1.11) |
| Precarious employment ratio | 0.07 (0.17) | 0.09 (0.17) |
| Women labor ratio | 0.13 (0.25) | 0.49 (0.22) |
| Child labor ratio[9] | | 0.06 (0.12) |
| Distance to major road (kilometers) | 18.43 (18.91) | 14.81 (23.05) |
| Access to credit (1=with access, 0=without) | 0.29 (0.45) | 0.04 (0.17) |
| Distance to the micro-finance office (kilometers) | 14.93 (16.59) | |
| Distance to nearest population center (kilometers) | 47.09 (43.53) | 39.06 (43.72) |
| Distance to the administrative capital (kilometers) | 141.75 (87.28) | 57.32 (58.53) |

Table 2 presents the descriptive statistics of the samples in Ethiopia and Tanzania. The average landholdings in Ethiopia and Tanzania are 1.25 and 3.34 hectares, respectively. The sample includes crop-livestock mixed production system, which has been practiced by most of the farm households. There is diversity in the production systems across regions of both countries. For instance, such diversity is clearly observed in differences in terms of livestock ownership: in mixed crop-livestock production systems few animals seem to be kept primarily for draft power requirements and risk coping strategy; whereas agro-pastoral households keep a relatively larger number of livestock (cattle) as their primary (and sometimes single) income source. The employment ratio is around 80% in both countries, which is a little lower than the average labor force participation reported by the World Economic Forum Report (2013) of about 86% in Ethiopia and 90% in Tanzania. Proportion of women participated in agricultural activities are14% in Ethiopia and 48% in Tanzania. Based on the data at disposal, child labor in the sample for Tanzania is about 6% of the total agricultural labor used by the household. The average proportion of employment in the precarious category to the total labor is 0.06 in Ethiopia and 0.09 in Tanzania.

[9] The dataset has few observations for this variable in Ethiopia

**Empirical framework and econometrics**

To examine the role of decent rural employment in agricultural production efficiency in smallholder farming context, we employ a single step approach integrating the production function and decent rural employment indicators. In our analytical framework, we use labor as an important input in the production process, and thus is used in the production frontier estimation. The construction of the production possibility frontier given a certain level of technology, either with parametric assumptions or with piecewise constructions, is the fundamental step in efficiency estimation (Coelli et al., 2005; Farell, 1957). Hence, a multi-output, multi-input production technology specification is required. Based on Farrell's work (Farell, 1957), the input-output transformation equation can be specified as:

$$S = \{(x, y) : x\ produces\ y\} \tag{1}$$

Where *S* is a certain technology, using input vector x to produce output vector y. In a parametric setting with more than one output, a Stochastic Distance Function (SDF), either input or output oriented can be employed for efficiency analysis. The SDF approach has a number of advantages over the deterministic approach as it can differentiate noise (e.g., weather variation, measurement error etc.) - which is relatively common in agriculture and in rural labor data - from technical inefficiency effects, accommodate more than one output and thus enables single-step efficiency estimation. Distance function can be represented in a mathematical model as:

$$d_i^I = d^I(x_{1i}, x_{2i} \ldots x_{Ni,} y_{1i,} y_{2i} \ldots x_{Mi}) \tag{2}$$

$$d_i^o = d^o(x_{1i}, x_{2i} \ldots x_{Ni,} y_{1i,} y_{2i} \ldots x_{Mi}) \tag{3}$$

Where equation (2) and (3) illustrate the respective representations of input and output oriented distance function ($d_i$) in a technological set of producing M number of positive outputs ($y = y_1, y_2, \ldots, y_M$) using N number of non-negative inputs ($x = x_1, x_2, \ldots, x_N$). The input oriented distance function (IODF) approach is based on the radial contraction of the input use of firms (farms, in this paper) that brings the farm to the isoquant. The output oriented distance function (OODF) approach on the other hand tries to find the radial expansion of the outputs while keeping the level of input use. In a perfect input and output market condition, using either an input oriented distance function or the output-oriented approach should lead to the same result. However, the estimation results might differ in practice. Kumbhakar et al. (2007) highlight that OODF is appropriate when outputs are endogenous and, IODF is preferred when inputs are endogenous. In the sub-Saharan agricultural production context, most smallholder producers are unable to meet the recommended input levels (Crawford et al., 2003; Poulton et al., 2006).

In such a context, the idea of reducing production input use to reach to the frontier level seem to be an unrealistic assumption (Ogundari and Brümmer, 2011). It is plausible to assume the possibility of radial expansion of outputs with the given level of inputs when economic entities aim to maximize their outputs (Cullmann and Zloczysti, 2014; Kumbhakar et al., 2007). Accordingly, we decide to use the output oriented distance function approach for the estimation. Lovell et al. (1994) specified an output oriented distance function with an underlying homogeneity as:

$$D_0(x, \mu y) = \mu D_0(x, y) \tag{4}$$

By choosing one of the outputs, for example M$^{th}$ output, we can re-write equation 4 as:

$$\ln(D_{0i}(x, y)/y_{Mi}) = lnf\left({}^{y_{mi}}/_{y_{Mi}}, x, \beta\right) \tag{5}$$

Where β is a vector of technological coefficients and i is an index for households. After simple mathematics and by replacing the distance parameter with the error term (a composition of the noise component $v_i$ and the inefficiency parameter $u_i$), it can be observed that this coincides with the classic stochastic specification of the input-output relationship.

$$-\ln y_{Mi} = ln\mathrm{f}\left({}^{y}/_{y_M}, \mathrm{x}, \beta\right) + v_i + u_i \tag{6}$$

The type of production technology, availability of data, sample size (to keep some level of degree of freedom) and the requirements of the estimation procedures are crucial to determine the aggregation levels (Coelli and Perelman, 2000; Coelli et al., 2005; Kumbhakar and Lovell, 2003). Farm households engage in diverse range of crop and livestock production activities. It is often a challenge to incorporate all inputs and outputs in the estimation. These challenges include data availability, multicollinearity between different coefficients, smaller sample size and low level of degrees of freedom. It is rather a common practice to aggregate the outputs and inputs; and one of the options suggested in empirical literature is the use of implicit quantity indexes (Brümmer et al., 2002). It is a common practice to use value expressions as proxies for non-observed quantities (Brümmer et al., 2002; Chavas et al., 2005; Solís et al., 2009). In our estimation, we aggregate the outputs as the annual production implicit quantity index of crop harvest and livestock production per household. In order to reach to these volume measures, current values are deflated by the price indices. We deflate the output measured with current monetary value by the price index in each country in 2011 to derive the respective implicit output quantity index. The implicit value index can't fully take out the price information from the value terms, and the allocative inefficiency[10] could still remain part of the technical inefficiency estimate. Due to the imperfect and less developed input markets (for instance land, or financial markets) or output markets in sub-Saharan Africa, we didn't particularly aim to calculate the allocative inefficiency of farms. We use cultivated land per household (in hectares), family labor (measured in working days in agricultural activities), intermediate inputs[11], capital expenditure[12] and livestock (in Tropical Livestock Unit) without separating their contribution to draft power or direct output as production inputs. We use a translog functional form as it is more flexible in its form and is widely used in empirical studies (Coelli and Perelman, 1999; Sauer et al., 2006). In addition, some of the functions, such as Cobb-Douglas violate important curvature properties (e.g., convexity) (Coelli and Perelman, 2000; Färe et al., 2005). Accordingly, we employ the empirical model of the multi-input and output production frontier with translog specification.

$$-\,ln\,y_{1i} = \alpha_0 + \sum_{m}^{M} \alpha_m lnx_{mi} + 0.5 \sum_{m_j}^{M} \sum_{m_g}^{M} \beta_m lnx_{m_j i}\, lnx_{m_g i} + \sum_{n}^{N-1} \beta_m ln\left(\frac{y_{ni}}{y_{1i}}\right) + \sum_{n}^{N-1} \sum_{m}^{M} \delta_{nm} ln\left(\frac{y_{ni}}{y_{1i}}\right) lnx_{mi} + \; v_i + u_i \qquad (7)$$

With the distributional assumption of Aigner et al. (1977) for the two error components, v and u, and a follow-up application of maximum likelihood technique, we can single out the efficiency estimates. Aigner et al. (1977) assume that the error term (v) is iid N(0, $\delta_v^2$) - independently and identically distributed with mean zero and standard deviation $\delta^2$. According to Battese and Coelli (1995), with a more generalized assumption of truncated normal distribution, u are iid $N^+(\mu, \delta_u^2)$ – independently and identically distributed half normal random variables with a scale parameter $\delta_u^2$. Finally, technical efficiency of farm households in the production of mixed outputs will be calculated as:

$$TE_0 = \exp(-U_i^+) \qquad (8)$$

Battese and Coelli (1995) developed a single step maximum likelihood procedure to estimate both the frontier and inefficiency specification. This can be done by integrating the following equation to the one in equation (7).

[10] We are grateful to one of the anonymous reviewers for pointing this out.

[11] Summarizes seed, fertilizer, chemicals, wage, draft power rent etc. used for production

[12] Capital expenditure includes purchase of live animals, investments on perennial trees or machineries

$$\mu_i = \alpha_0 + \sum \alpha_n Z_{ni} + \varepsilon_i \tag{9}$$

$\mu_i$ is the conditional mean of $u_i$ from the first estimation procedure, $\varepsilon_i$ is the statistical noise, and α´s are the unknowns that will be estimated in the procedure. $Z_i$´s include the set of decent rural employment indicators (as defined in section 2, table 1) and a vector of other control variables (age and sex of the household head, age dependency ratio, concentration index, access to credit, regional dummies). We employ two indicators, namely the Ogive index and Herfindahl index, for measuring the diversification level of farms. These indicators measure the deviation from full diversifications (equal distribution of output shares) among production activities. A higher value (one in Herfindahl index and two in Ogive index) reflect concentration (or complete specialization) of a firm, while zero represents full diversification.

There are a number of econometric challenges in the estimation. First, this estimation procedure could suffer from endogeneity. In the OODF, this can arise from the possible endogeneity of the output terms in the right-hand side of the equation (Coelli et al., 2005; Kumbhakar and Lovell, 2003). However, only the ratios of the outputs are used as explanatory variables in the specification and are assumed exogenous (Brümmer et al., 2002; Coelli and Perelman, 1999). In the formulated specification, we are dealing with radial expansion or contraction of outputs and inputs respectively, and these ratios are constant for each term (Coelli and Perelman, 1996). There are also questions raised on the validity of these assumptions (Kumbhakar, 2011; Kumbhakar and Lovell, 2003; Tsionas et al., 2015). The issue of endogeneity of the output (or the output ratio) seems unsettled and remains a point of active research (Brümmer et al., 2002; Kumbhakar, 2011; Tsionas et al., 2015). Second, some inputs in the right hand side of the estimation (equation 7) might be endogenous (Kumbhakar, 2011; Kutlu, 2010; Shee and Stefanou, 2014; Tsionas et al., 2015). Land is a public property in both countries, and farmers are less likely to adjust farm land to productivity shocks. With the existing imperfect credit and financial markets in most sub-Saharan African countries, smallholders are constrained to adjust for positive or negative productivity shocks (Barrett et al., 2008). However, the story could be different for labor input in smallholder agriculture. As households can have surplus labor, farms might be able to adjust in responses to productivity shocks. If such an adjustment exists, the model is likely to suffer from endogeneity bias. To control for such unobserved effects, various econometric approaches are suggested often with the application of instrumental variables (Kim and Kim, 2011; Kutlu, 2010; Shee and Stefanou, 2014; Wooldridge, 2009). As smallholder farms labor often consists of family labor for agricultural production activities, family size can be used as an instrument for labor input. Sonoda and Mishra (2015) for instance used the number of family members that can work in the farm as an instrument for labor. If there exists positive productivity shock, the family members who otherwise might not work in the farm could join in to the business. Third, one has to take care of the likely endogeneity in the inefficiency model (equation 9). For instance, efficient farms can have a better access to credit services, and this can lead to biased estimation. For this, we use distance to the population center and district capital in both countries, and distance to the micro-finance service provider[13] in Ethiopia as instrument for credit access. Accordingly, in addition to the usual single step maximum likelihood approach, equations (7) and (9) are estimated using an instrumental variable General Method of Moments (GMM) approach with an optimal weighting matrix (Wooldrige, 2009).

## IV. Results and discussions

### The production function estimation

The maximum likelihood (ML) and GMM results of the Output Oriented Distance Frontier estimation are presented in Table 3. Prior to the estimation, all the respective output and input variables are standardized (corrected by the geometric mean) so that the first order coefficients can be interpreted as distance elasticity evaluated at the geometric mean (Kumbhakar et al., 2007; Solís et al., 2009). According to the likelihood ratio test, we reject the more restrictive Cobb-Douglas specification. The residuals of our estimation results are negatively skewed and likelihood ratio test rejects the null hypothesis of absence of inefficiency component. Hence, the technical inefficiency component is a statistically significant addition to the model. One of the crucial steps after estimating the production function is to check whether the fitted model violates any major assumption of parametric approaches (Kumbhakar and Lovell, 2003; O'Donnell and Coelli, 2005; Sauer et al., 2006). With the exception of intermediate inputs in Tanzania, the coefficients of the input variables are significant and have the expected signs at the geometric mean, fulfilling the assumption of monotonicity[14]. In other words, our estimated output oriented distance function is non-decreasing in output. The instruments used are strong as shown in the Cragg-Donald F-statistic in the first stage (313.9 for Ethiopia and 127.3 for Tanzania). Despite some differences in the magnitude and significance of the input parameters, the ML and IVGMM estimation approaches result in similar specifications.

[13] This information is not available for Tanzania

[14] Monotonicity in this case is interpreted as the non-decreasing property of the function.

Table 3: production function specification (dep.var: Total crop harvest)

| Variables | Ethiopia | | Tanzania | |
|---|---|---|---|---|
| | Max. likel. | GMM | Max. likel. | GMM |
| land | -.155$^{***}$(.050) | -.210$^{***}$(.048) | -.249$^{***}$ (.032) | -.242$^{***}$(.034) |
| Intermediate inputs | -.081$^{***}$(.026) | -.019 (.025) | .038 (.034) | .017 (.033) |
| labor | -.094$^{***}$(.027) | -.114$^{***}$(.027) | -.281$^{***}$(.034) | -.259$^{***}$(.037 |
| livestock | -.251$^{***}$(.046) | -.248$^{***}$(.054) | -.084$^{***}$(.022) | -.116$^{***}$(.025) |
| capital expenditure | -.079$^{***}$(.014) | -.123$^{***}$(.018) | -.167$^{***}$(.029) | -.161$^{***}$(.029) |
| lives_crop_ratio | .131$^{***}$(.015) | .123$^{***}$(.017) | .199$^{***}$(.017) | .206$^{***}$(.019) |
| land*land | .053$^{*}$ (.028) | .054$^{*}$(.028) | .013 (.017) | .010 (.018) |
| int. input*int. input | -.019$^{*}$ (.011) | -.023$^{*}$ (.012) | -.019 (.012) | -.025$^{**}$(.012) |
| labor*labor | .004 (.016) | .008 (.015) | .008 (.021) | .003 (.019) |
| livestock*livestock | -.029$^{*}$ (.016) | -.016 (.017) | -.006 (.007) | .007 (.008) |
| capital*capital | -.008$^{***}$(.002) | -.013$^{***}$(.002) | -.014$^{***}$(.002) | -.014$^{***}$(.003) |
| land*int.input | -.014 (.033) | .017 (.029) | -.021 (.021) | -.024 (.023) |
| land*labor | -.025 (.041) | .019 (.041) | -.036 (.029) | -.012 (.015) |
| land*livestock | .072 (.062) | .099 (.065) | -.001 (.012) | -.004 (.013) |
| land*capital | -.0013 (.008) | -.025$^{***}$(.008) | -.014$^{**}$(.006) | -.013$^{**}$(.005) |
| land* lives_crop_ratio | -.019 (.023) | -.034 (.026) | .012 (.014) | .026 (.016) |
| int.input*labor | .022 (.023) | .004 (.021) | .002 (.023) | .012 (.024) |
| int.input*livestock | -.022 (.021) | -.041 (.031) | .006 (.009) | .002 (.011) |
| int.input*capital | .009$^{*}$ (.005) | .015$^{***}$(.005) | .015$^{***}$(.005) | .017$^{***}$(.005) |
| int.input*lives_crop_ratio | -.005 (.012) | .001 (.013) | .001 (.011) | -.006 (.016) |
| labor*livestock | -.006 (.038) | -.041 (.039) | .008 (.014) | .012 (.015) |
| labor*capital | -.003 (.006) | -.001 (.006) | .010 (.006) | .010 (.007) |
| labor*lives_crop_ratio | .037$^{***}$(.013) | .048$^{***}$(.013) | -.031$^{**}$(.016) | -.034$^{*}$ (.019) |
| livestock*capital | .001 (.001) | .006 (.008) | -.002 (.003) | -.003 (.003) |
| livestock*lives_crop_ratio | .003 (.019) | -.014 (.021) | .001 (.006) | -.002 (.007) |
| capital* lives_crop_ratio | -.002 (.003) | -.005 (.004) | -.002 (.003) | .001 (.003) |
| Model summary for IV GMM | Cragg.Don. F=313.9, Anderson canon. LM=670.281, p= 0.000 | | Cragg-Don.F=127.3, Anderson canon. LM=427.58, p= 0.000 | |

Note: *, **, and *** represents 10, 5, and 1% level of significance. Regional dummies are not reported to save space.

**Determinants of technical efficiency: The role of decent rural employment**

Estimation of inefficiency determinants in both with the joint estimation using the maximum likelihood (ML) and the GMM approach show similar pattern. Distance to the population center, to the district capital and to the micro-finance service provider are the instruments used for the estimation in Ethiopia. We similarly employ distance to the population center and to the district capital as instruments in Tanzania.

The Cragg-Donald F-statistic in the first stage (30.06 for Ethiopia and 14.31 for Tanzania) of the instrumental variable model confirm the relevance of instrument. The weak identification test hypothesis is also rejected (Anderson canon. LM statistic of 29.79 and p = 0.00 for Ethiopia, and Anderson canon. LM statistic of 81.73 and p = 0.00 for Tanzania). Despite the difference in the magnitude in some of the variables, the maximum likelihood estimation and the IV GMM results show similar pattern. This shows that, the change in the estimation doesn't affect the interpretation much. In what follows, we present the determinants of inefficiency from the maximum likelihood and IV GMM estimations. We do find evidence that most of the decent rural employment indicators influence the production efficiency of smallholder farmers. This effect is robust and stay important after we control for unobserved heterogeneity in the IV GMM approach.

Table 4: Determinants of inefficiency

| | Ethiopia | | Tanzania | |
|---|---|---|---|---|
| Variables | Max. LH | IV GMM | Max. LH | IV GMM |
| Annual precipitation | .002 (.002) | .002 (.002) | .001 (.001) | -.001 (.001) |
| Prec. of wettest quarter | -.001 (.001) | -.001 (.001) | .002 (.002) | .002 (.003) |
| Sex of household head | -.306 (.273) | -.077 (.054) | $-1.38^{**}$(.61) | $-.182^{***}$(.043) |
| Age of the head | .001 (.005) | -.001 (.001) | -.005 (.009) | -.001 (.002) |
| Household head literacy | $-.466^{***}$(.15) | $-.183^{***}$(.037) | -.102 (.087) | $-.012^{**}$(.006) |
| Age dependency ratio | -.047 (.085) | -.020 (.017) | $-.282^{*}$ (.170) | $-.044^{***}$(.015) |
| Herfindahl index[15] | $2.78^{***}$(.52) | $.988^{***}$(.113) | .611 (.783) | .117 (.151) |
| Share of gov. transfer | $-3.534^{*}$(2.06) | $-.221^{***}$(.05) | $-6.31^{**}$(2.81) | $-3.49^{***}$(.755) |
| Access to credit | $-.301^{*}$ (.161) | -.063 (.176) | .064 (.778) | -.364 (.551) |
| Emp. to workforce ratio | $-.641^{***}$(.27) | $-.302^{***}$(.007) | -.051 (.518) | .054 (.080) |

[15] The estimation result of the Ogive Index is not reported here to save space.

| | | | | |
|---|---|---|---|---|
| Precarious emp. ratio | 1.87***(.49) | .744***(.188) | 1.92***(.682) | .429***(.086) |
| Women labor ratio | .151 (.348) | .083 (.079) | .501 (.733) | .040 (.065) |
| Child labor ratio | | | 2.82***(1.08) | .573***(.186) |
| Model summary for IV GMM | Cragg-Don. F=30.06, Anderson canon. LM=29.79,p-value= 0.00 | | Cragg-Don. F=14.31, Anderson canon. LM=81.73,p-value= 0.00 | |

Note: Number of observations= 1023 for Ethiopia, and 931 for Tanzania. *, **, and *** represents 10, 5, and 1% probability level. Regional dummies are not reported to save space.

In the case of Ethiopia, employment to family members available for work ratio has positively contributed to the household production efficiency. The effect is lower in magnitude when we control for unobserved heterogeneity. Rao et al. (2004) have found similar results in their study of productivity and the productive employment relationship from a macro perspective using data from 111 countries. Investing in the creation of employment opportunities for the available labor force is particularly pertinent in sub-Saharan Africa. The available options should on the one hand, be productive to the producers and employers, and on the other hand, should help to improve the living conditions of workers and their families.

Table 4 also show that precarious employment magnifies technical inefficiency in both countries. A model without controlling for unobserved heterogeneity seem to overestimate the effect of precarious employment in both countries. Given the inherent labor characteristics of smallholder agriculture in sub-Saharan Africa (e.g., labor intensive technologies, farms operated by household members), employment options in the agricultural sector are largely limited to peak seasons, and are often casual. Furthermore, there are limited off-farm and non-farm employment opportunities available in rural areas of Ethiopia and Tanzania, and when available, they often are of low quality. Rural employment opportunities are significantly limited to seasonal and casual forms of agricultural and non-farm wage work, which is mainly undertaken by the landless and other resource poor workers. In an overall low productivity setting, these low paid, precarious and less motivating forms of employment could be detrimental to the overall agricultural efficiency. This at least requires serious control and monitoring mechanism, which in turn increases the cost of production.

In Tanzania, child labor contributes to higher inefficiency in agricultural production. The effect is lower (2.82 reduces to 0.573) when we control for unobserved heterogeneity. In using child labor for agricultural activities, the household gets comparatively low levels of returns had it been from adult labor. This result is in line with the finding of Sherlund et al. (2002). The finding by Sherlund et al. (2002) reported that the output response from added child labor was one third relative to added adult labor. Furthermore, our finding is in line with overall recognition that child labor should be prevented from a human rights perspective and also because it perpetuates a cycle of poverty for the children involved, their families and the community as a whole (FAO, 2015)[16].

In both countries, transfers received from social protection programs significantly contribute to improve agricultural efficiency. The effect is still strong, but lower in magnitude when we control for unobserved heterogeneity. This finding in line with existing evidence around the positive impacts of public in-kind and cash transfers to rural households in sub-Saharan Africa (Boone et al., 2013; Gilligan et al., 2008; Hoddinott et al., 2012). Such positive effects could be explained in two ways: either the cash transfer is used for agricultural investments or it contributes for consumption smoothing which in turn improves the production capacity of farm households (Asfaw et al., 2014; Boone et al., 2013). Improved social protection in the developing world might contribute towards improving liquidity constraints and prevent families from falling into poverty traps, which is the classical problem in both countries.

Other control variables also explain some of the inefficiency puzzle in the two countries. In Ethiopia, we do find that higher household concentration or specialization is associated with higher inefficiency in agricultural production. This result is consistent when we employ either Herfindahl index or Ogive index for measuring production diversification. However, the magnitude is lower when we use the instrumental variable technique. Production inefficiency varies with the sex of the household head and age dependency ratio in the household in Tanzania. Though access to credit in Ethiopia seem to contribute to the production efficiency, the relationship is not there when we control for unobserved heterogeneity. Hence, we argue that, this effect might come from unobserved heterogeneity from the selection in the credit market. Additionally, literate household heads are more likely to be technically efficient in agricultural production than the illiterate counterparts.

**Scale, scope and technical efficiency estimates in Ethiopia and Tanzania**

We do find a wide variation in the technical efficiency level of smallholder farmers in Ethiopia and Tanzania, with mean efficiency estimate of about 60% and 78%, respectively. This finding is in line with technical efficiency scores estimated by many empirical findings in sub-Saharan

[16] Data at disposal do not allow for further analysis of child labor in terms of types of agricultural tasks assigned to children, their relative time intensity and potential occupational hazards, and thus we cannot conclude about any potential conflict with schooling (attendance and performance) or specific risks for the children's health and development.

Africa and the developing world (Alene and Zeller, 2005; Solís et al., 2009) and averages from meta-analysis studies in Africa (Bravo-Ureta et al., 2007; Ogundari, 2014; Ogundari and Brümmer, 2011). For instance, a meta-regression analysis by Ogundari (2014) found an average technical efficiency of 68% using 442 frontier studies in sub-Saharan Africa. Our results indicate that there is potential to improve the farms' technical efficiency with the available resources and technology. The elasticity of the output ratio captures the proportion of the output from the total output produced (Brümmer et al., 2002; Newman and Matthews, 2006). With a slight difference across the two models, the coefficients of the livestock output ratio are 0.13 and 0.20 in Ethiopia and Tanzania, respectively. The positive sign on the livestock to crop output ratio indicates the presence of trade-off for the given level of inputs between crop and livestock activities. With the homogeneity constraint in the outputs, the elasticity of the output used as a reference bundle (crop) will be the rest. This tells us that crop production constitutes the major share of the total output (87% and 80%) in Tanzania and Ethiopia.

The negative of the sum of the input elasticity (coefficients) in the model can be used to calculate the scale elasticity (Coelli and Perelman, 1996; Kumbhakar et al., 2007). For instance using the ML approach, input elasticities are 0.155, 0.081, 0.094, 0.251 and 0.079 for land, intermediate inputs, labor, livestock units and capital respectively for Ethiopia; and 0.249, 0.281, 0.084 and 0.167 for land, labor, livestock units and capital respectively for Tanzania. A scale of elasticity of 0.64 for ML and 0.71 for IV GMM in Ethiopia, and 0.78 for both estimation methods for Tanzania reveal the presence of decreasing returns to scale (DRTS) in agricultural production (Table 3). Existing empirical papers present mixed findings with respect to the returns to scale in the developing world. The works of Chavas et al. (2005) in Gambia and Solís et al. (2009) in Central America reported DRTS in multi-input and output estimation procedure. Anriquez and Daidone (2010) on the other hand found increasing returns to scale (IRTS) in Ghana. This is often associated with the existence of imperfect markets, where farmers lack flexibility of allocating resources to alternative production activities. This sub-optimality can arise from the use of some of the inputs in the production process (such as surplus labor) beyond the optimal level. In sub-Saharan Africa, factor markets are less developed and weakly functional and hence they pose limits to the flexibility that farm operators have for resource allocation (Anriquez and Daidone, 2010; Barrett et al., 2008; Chavas et al., 2005).

Though the sample is dominated by crop-livestock mixed agricultural households, it consists of semi-pastoral households with an extensive farming systems in Ethiopia, and households that engage in fishery activities in Tanzania. Hence, one can expect that the marginal productivity of land could be lower compared to farms with intensive agriculture. This is in line with empirical findings in Africa and elsewhere in the world. For instance, Irz and Thirtle (2004) found a scale efficiency of land of 0.11 in a mixed crop livestock sample in Botswana. Likewise, Newman and Matthews (2006) have found out the elasticity of land that ranges from 0.12 in Ireland to 0.33 in Netherlands in dairy farms. One has to be cautious in interpreting the result as the production elasticity of inputs can vary across different production systems and farming conditions.

## V. Concluding remarks and policy implications

The paper analyses whether decent rural employment can contribute to efficiency in agricultural production. The relationship has been verified, and the finding shows a significant relationship, as captured by a set of decent rural employment indicators (i.e., employment to workforce available ratio, share of public transfers to the total income of the farm household, proportion of precarious employment to the total employment, and child labor ratio) and technical efficiency of farms. To the best of our knowledge, this paper has been the first in its type to explicitly raise the issue and role of precarious employment in the efficiency of smallholder agriculture. Precarious forms of employment and the prevalence of child labor ratio prevent smallholder farms from achieving greater technical efficiency. Our findings emphasize that supporting more productive and decent farm and on-farm employment (i.e., self-employment, or wage employment), and creating more productive and decent rural non-farm employment opportunities for the rural workforce by and large can lead to a win-win situation for sub-Saharan Africa smallholder agriculture in terms of efficiency gains in farm production and job creation. Governments and other organizations should support policies and programs that increase decent rural employment opportunities both in agricultural and the non-farm sector in sub-Saharan Africa. These attempts can reduce rural poverty by simultaneously improving agricultural production efficiency and rural livelihoods. As our findings suggest, there are significant differences across farm units and rural settings, which needs to be accounted for in the design of such interventions. Finally, future research can further elaborate the findings of this paper with improved rural labor data, especially using panel datasets, and thus enrich the analysis by expanding to other dimensions of decent rural employment.

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## 4. Farm diversification and the cost of risk in smallholder agriculture: Panel data evidence from Ethiopia

With Johannes Sauer and Getachew Abate-Kassa

**Abstract**

This paper analyzes the implication of the cost of risk on farm diversification decision in smallholder agriculture using an unbalanced panel data from Ethiopia. The cost of risk exposure is estimated using a moment based approach in a fixed effects panel data model using flexible quadratic specification. In the second stage, we test if the estimated cost of risk explains part of the farm diversification puzzle by including it together with agro-ecological, socio-economic, institutional and organizational factors as controls. In addition, we do find an evidence that the cost of risk influences the level of farm diversification in smallholder agriculture in Ethiopia. Smallholder farmers, with little or no option to engage in market-based risk management strategies, invest in a more diversified production to mitigate risk. This evidence substantiates the need for consideration of the issue of risk in policies targeted towards enhancing farm specialization in the developing world.

Keywords: cost of risk, diversification, risk management, smallholder

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### I. Introduction

Farm diversification is among the widely discussed topics in agriculture and rural development (Chavas, 2004; Chavas and Di Falco, 2012; Di Falco and Chavas, 2009; Hardaker et al., 2004). Some evidences were found on the productivity enhancing role of specialization through economies of scale (Kurosaki, 2003; Larson and Plessmann, 2009). Economies of scope and jointness of production on the other hand give an incentive for diversification (Chavas and Di Falco, 2012). In addition, diversification can offer numerous advantages including risk mitigation and ecological benefits (De Groot et al., 2002; Di Falco and Chavas, 2009; Finger and Buchmann, 2015).

Recent papers analyzed and documented the role of biodiversity in reducing vulnerability of farmers to risk in Ethiopia. Di Falco and Chavas (2009) and Chavas and Di Falco (2012) are influential ones in this regard. Di Falco and Chavas (2009) found skewness effect of biodiversity dominates its variance effect, and contribute to reduce risk in Ethiopia. Similarly, Chavas and Di Falco (2012) documents the welfare contribution, both to productivity and risk, of crop diversification.

The occurrence of a climate change, price volatility can disturb the resource base of the community and influence the overall societal wellbeing (Bellemare et al., 2013; Eakin, 2005; Gloede et al., 2015). The effect is substantial in agriculture, as climate variabilities may exacerbate production risk (Solomon, 2007) and commodity prices are often volatile (Bellemare et al., 2013; Fjelde, 2015). Smallholder farmers in sub-Saharan Africa often face climate variabilities with adverse welfare effects (Dercon, 2004; Randell and Gray, 2016). Ethiopia, for instance, has experienced a couple of major famines in recent decades with disastrous consequences (Dercon, 2004; Di Falco and Chavas, 2009; Morrissey, 2013).

Agriculture is inherently risky and a risk averse farmer will explore ex-ante risk mitigation or ex-post adaptation strategies to reduce the pervasive effects of risk. Farmer's responses for risk can be of ex-ante or ex-post. Farmers with severe shock experiences might consider sub-optimal resource allocation decisions. Smallholder farmers in Ethiopia, for example, reduce fertilizer use (Alem et al., 2010) or consider sub-optimal land rental deals as a response to shocks (Gebregziabher and Holden, 2011). Ex-ante production risk management strategies are crucial in smallholder agriculture as market and other institutional mechanisms are lacking or underdeveloped. This risk mitigation schemes include farm diversification and biodiversity, soil and water conservation schemes, irrigation (Di Falco and Chavas, 2009; Groom et al., 2008; Kato et al., 2011). One of the key responses of smallholder farmers for shock in a production activity could be to diversify farms and non-farm activities.

There are attempts that document the factors that influence diversification decisions in Ethiopia (Benin et al., 2004). Despite little focus of empirical works, shock experience and cost of risk are among the major reasons that influence diversification decisions in agriculture (Hardaker et al., 2004; Kandulu et al., 2012). Related paper in this regard is the work of Bezabih and Sarr (2012) that report the implication of risk perception on crop diversification decisions in Ethiopia. However, they use experimental approach to predict risk perception of farmers, and their work didn't specifically attempt to measure the role of the cost of risk. Specifically, there is no study done to analyze the effect of the cost of risk and risk exposure on the farm diversification decision of households and is of special interest here. In this paper, using a panel data of smallholder farms from Ethiopia, we find a strong evidence that the cost of risk covers a significant percent of the farm income. Furthermore, we show that the cost of risk influences the farm diversification decision of the household.

## II. Empirical Approach

Consider a farm household in a developing country with multi-input and output production option, given a wide range of constraints. The basic analytical framework is an optimization problem of the farm household, whether to diversify or specialize on certain agricultural activity, given the physical, socio-economic, institutional, and organizational constraints.

Following on previous empirical endogenous technology adoption models under risk (Groom et al., 2008; Zuo et al., 2014), we employ a farm household model to analyze the factors that might determine the level of farm diversification. Accordingly, farm diversification is expressed in a function given the cost of risk and other control variables as:

$$D_{it} = f(\alpha Z_{it} + \beta R_{it} + \delta L_{it} + \gamma O_{it}) \tag{1}$$

Diversification of a household at a given time is expressed as a function of household specific demographic and socio-economic variables ($Z_{it}$), the cost of risk exposure ($R_{it}$), land quality, fragmentation and location related factors ($L_{it}$) and other institutional and organization related factors ($O_{it}$). An important challenge in the estimation of the above equation is how to find the cost of risk exposure at the household level.

Farmers dealing with an uncertain environment consider both the expected profit and the level of risk associated with the alternative choices in their decisions. The expected utility of profit can be represented by a simple function integrating the expected value of profit and the risk element as:

$$EU(\pi) = U[E(\pi) - RP] \tag{2}$$

The right-hand side of equation (2) is defined as the certainty equivalent of profit ($CE = E(\pi) - RP$) (Kimball, 1990; Pratt, 1964). A risk-averse individual is willing to pay an implicit cost to eliminate risk – called risk premium (Arrow, 1965; Pratt, 1964). The risk premium of the household measures the positive amount of money that he/she is willing to pay for risk mitigation mechanisms (Chavas, 2004; Pratt, 1964). This framework allows us to calculate the certainty equivalent of the farm from the first and other higher level moments of the profit function (Antle, 1983; Chavas and Di Falco, 2012).

Reduced form of the production function with respect to farm inputs can be represented as:

$$y_{it} = f(X_{it};\beta) + u_{it} \tag{3}$$

where $y_{it}$ represents the aggregated gross margin per hectare from farm production of the household (i) in year (t) using the vector of farm inputs, $X_{it}$. We use three major agricultural inputs (cost of seed, labor and other intermediate inputs[17]) common in smallholder production systems. We aggregate these inputs per hectare of land used for production purposes. To increase the model fit and robustness, and to facilitate further use of the marginal effects in the risk parameter estimation, all the variables are rescaled by their standard deviations.

The basic premise in the moment-based approach is to capture the risk attitude of the household in the residual of the estimation ($u_{it}$), which is assumed to have a zero mean and variance ($\delta^2$). The residuals of equation (3) are then used to estimate the second (variance) and third (skewness) order moments of profit distribution.

$$\hat{u}_{it^2} = g(X_{it};\alpha) + \breve{u}_{it} \tag{4a}$$

$$\hat{u}_{it^3} = h(X_{it};\gamma) + \tilde{u}_{it} \tag{4b}$$

Following Arrow (1965) and Pratt (1964), the risk premium from the Arrow-Pratt absolute risk aversion (AP) and downside risk aversion (DS) can be calculated from the higher order functions.

$$RP = r_2 Var(y)/E(y) + r_3 Skew(y)/[(E(y)^2)] \tag{5}$$

Where $r_2$ and $r_3$ are the risk aversion parameters of individuals to absolute risk (AP=$r_2 Var(y)/E(y)$) and downside risk (DS=$r_3 Skew(y)/[(E(y)^2)]$). A positive AP value (*AP>0*) indicates a risk-averse decision maker. A risk-averse farmer is willing to pay a positive amount of money to reduce the variability of profit. If DS is positive (*DS <0*), the average farmer is averse to low income levels (for example, crop failure) (Chavas and Di Falco, 2012; Menezes et al., 1980). Finally, we need to know the risk preferences of the farmers ($r_2$ and $r_3$ ) to compute the risk premium of the farm. Though the risk preferences are specific to the farmer, in a constant relative risk aversion (CRRA) assumption, empirical works find out that this value

[17] Intermediate inputs include costs of fertilizer, pesticides and hired labor

vary from 1(mild risk averse) to 4 (an extreme risk aversion) (Gollier, 2001). Most farmers in the developing world are risk averse (Chavas and Di Falco, 2012; Groom et al., 2008). Accordingly, we take the risk aversion parameter of 1 for this empirical investigation.

We calculate farm diversification (equation 1) using the Ogive index (Ali et al., 1991). This approach has advantages over count index as it captures intensity of diversification.

$$Ogive = \sum_{n=1}^{N} \frac{\left(A_n - (1/_N)\right)^2}{1/_N} \tag{6}$$

Where N is the total production activities and $A_n$ is the share of the total land allocated for the production activities (cereal crops, pulse crops, horticultural crops, tree and grass production). This index measures the deviation of the overall farm plan from equal allocation of the farmland among these different production activities. A value approaching zero indicates perfect diversification of production activities by the household (on cereal, pulse crops, horticulture crops, tree and plantations and livestock production). A value approaches to four indicates specialization in one of the farm production activities.

We use the Simpson Index (SI) (Blarel et al., 1992), which gives an advantage over the count index by capturing the evenness of land fragmentation in the household.

$$SI = 1 - \sum_{1}^{i} \frac{H_i^2}{H^2} \tag{7}$$

$H_i$ is the total area of the i$^{th}$ plot and $H$ is the total landholding of the farm household. SI is censored between 0 and 1, where 0 indicates the household produces all the farm outputs on one plot of land, while 1 indicates a higher level of land fragmentation. The diversification index is censored from both directions (ranges from zero for perfectly diversified farms to four for farms engaged in only one activity), and the Tobit model could be applied for equation (1).

Several econometric challenges might arise in the estimation of equation (3). One crucial step in the estimation procedure is to decide the functional form for the profit function (Antle, 1983; Groom et al., 2008; Kumbhakar and Tveterås, 2003). This is crucial because the results of the overall procedure are influenced by the choice of the functional form. For this, we employ a quadratic specification, which is considered as more flexible compared to other functional forms, and doesn't a priori limit the direction of effect of inputs on the mean, variance and skewness of profit. We use the input levels, their interaction terms and the square of the input levels as explanatory variables in this function. In the same way, we use the same approach and explanatory variables in the variance and skewness estimations (equation 4).

Second, unobserved heterogeneity (for instance suitability of the land for production or management ability) could lead to a biased coefficient estimation (Greene, 2002; Wooldridge, 2010). A panel data format enable us to control for time invariant unobserved characteristics of households. If this unobserved heterogeneity is time invariant, we can control this problem through the fixed approach effects approach. We estimate equation 3 with random effects approach and fixed effects approach. This could also be a problem for the function presented in equation (1).

Finally, there could be simultaneity between the risk premium calculated from the profit moments and farm management decisions (in this case, diversification) (Zuo et al., 2014). In order to control for the potential endogeneity problem, we use an instrumental variable technique (Wooldridge, 2010). We employ, the data on rainfall intensity at the onset and on the growing season and the lagged risk premium measure as instrumental variables. The instrumental variable should be adequately correlated with the endogenous variable, and should only influence the farm diversification decision through its effect on the endogenous variable. The first one is straight forward to verify, while the exclusion restriction is only plausible.

## III. Data and descriptive statistics

We use the Ethiopian Rural Household Survey panel data collected by the International Food Policy Research Institute (IFPRI) in collaboration with the Center for the Study of African Economies (University of Oxford) and the Economics department of Addis Ababa University. It is a rich panel dataset from smallholder farmers in 4 major regions in Ethiopia. The dataset consists of information related to household demographics and socio-economic characteristics, agricultural activities, production, consumption, marketing etc. We use the 2004 and 2009 rounds of survey for the analysis.

Table 1: Descriptive statistics

| ***Variable*** | Mean | Std. Deviation |
|---|---|---|
| Gross margin per hectare (in birr) | 19840.01 | 40244.89 |
| Seed per hectare (in birr) | 1047.31 | 3252.25 |
| Family labor per hectare (in man days) | 101.53 | 258.89 |
| Other inputs per hectare (in birr) | 261.31 | 607.58 |
| Age of the household head | 51.52 | 14.86 |
| Education level of the household head | 1.56 | 2.69 |
| Landholding (hectare) | 1.07 | 0.92 |

| | | |
|---|---|---|
| Land fragmentation (Simpson index) | 0.644 | 0.22 |
| Slope index of agricultural land | 1.307 | 0.548 |
| Soil fertility index | 1.618 | 0.742 |
| Off/non-farm income (in birr) | 399.14 | 1152.99 |
| Specialization (Ogive) index | 2.34 | 1.13 |

Table 2: Perception about rainfall

| | Percent | | |
|---|---|---|---|
| | Too little | Enough | Too much |
| Rainfall on the time of onset | 28.45 | 62.04 | 9.22 |
| Rainfall for growing season | 26.31 | 65.78 | 7.57 |

**IV. Estimation of profit moments and the cost of risk**

We estimate the profit function with the quadratic specification using a random effect and fixed effects approaches. The Hauseman specification test (with chi2 value=147.66 and p-value=0.000) rejected the null hypothesis of no systematic difference between random and fixed effect models. This test verifies that the estimation can be biased if we do not control for the individual fixed effect in the estimation. We also check the Feasible Generalized Least Squares (FGLS) estimation and the result is similar to the one estimated with the random effect procedure. Accordingly, we use the estimation results of the fixed effects estimator for interpretations and discussions in this paper. The results of the estimation of the mean function using alternative models is presented in Table 3.

Most covariates used in the estimation have the expected sign and the overall statistical significance of the estimated model is good. The coefficients associated with farm inputs, their interaction terms and the square terms do significantly explain the gross margin (the first moment) equation. The results of the fixed-effect estimation of the second moment (variance function) and third moment (skewness function) are presented in table 4.

Table 3: Random vs fixed effects of the mean function

| Variables | FGLS | Random effect | Fixed effect |
|---|---|---|---|
| Seed | -0.163*** (0.008) | -0.176***(0.048) | -0.415***(0.074) |
| Family labor | 0.253*** (0.007) | 0.287***(0.039) | 0.155***(0.057) |
| Other inputs | 0.096*** (0.004) | 0.092*** (0.036) | 0.277***(0.068) |
| Seed*Seed | 0.026*** (0.001) | 0.027***(0.007) | 0.053***(0.010) |

| | | | |
|---|---|---|---|
| Labor*Labor | -0.025$^{***}$ (0.004) | -0.014$^{***}$(0.003) | -0.022$^{***}$(0.004) |
| Other input* Other input | -0.001 (0.001) | 0.002 (0.004) | -0.008 (0.007) |
| Seed*labor | 0.027$^{***}$ (0.007) | 0.019$^{***}$(0.006) | 0.029$^{***}$(0.008) |
| Seed*other inputs | -0.019$^{***}$(0.005) | -0.023$^{***}$(0.009) | -0.051$^{***}$(0.013) |
| Labor*other inputs | 0.019$^{***}$(0.003) | 0.007 (0.005) | 0.025$^{***}$(0.007) |
| Year dummy | 0.207$^{***}$(0.005) | 0.256$^{***}$(0.039) | 0.297$^{***}$(0.045) |

N =2724, $^{*}$ if p<0.10, $^{**}$ if p<0.05, $^{***}$ if p<0.01. The values in brackets represent standard errors.

Table 4: Fixed effect estimates of the variance and skewness functions

| Variables | Variance | Skewness |
|---|---|---|
| Seed | -1.401$^{***}$(0.409) | -8.624$^{***}$(3.135) |
| Family labor | 0.765$^{***}$(0.319) | 5.930$^{**}$(2.444) |
| Other inputs | 0.912$^{***}$(0.319) | 6.349$^{**}$(2.855) |
| Seed*Seed | 0.173$^{***}$(0.057) | 0.944$^{**}$(0.440) |
| Labor*Labor | -0.061$^{***}$(0.023) | -0.557$^{***}$(0.178) |
| Other input* Other input | -0.066$^{*}$(0.038) | -0.615$^{**}$(0.287) |
| Seed*labor | -0.031 (0.045) | -0.121 (0.345) |
| Seed*other inputs | -0.065 (0.069) | -0.233 (0.535) |
| Labor*other inputs | 0.074$^{*}$(0.041) | 0.764$^{**}$(0.312) |
| Year dummy | 1.169$^{***}$(0.251) | 7.398$^{***}$(1.922) |
| Hauseman test (Chi2) | 133.02$^{***}$ | 101.90$^{***}$ |

N =2724, $^{*}$ if p<0.10, $^{**}$ if p<0.05, $^{***}$ if p<0.01. The values in brackets represent standard errors.

The inputs used in agricultural production, their squares and interaction effects are significant in the variance and skewness estimations. The effects of farm inputs to the variance function are mixed for Ethiopian farms. While some inputs and their non-linear effects are variance increasing (for example, family labor, other inputs, seed*seed etc.), others (for instance, seed, labor*labor etc.) are variance decreasing. This implies that the cost of risk from the variance function is determined by the type and intensity of farm inputs. The same is true for the case of the skewness function. Except for the case of seed, the squares of labor and other inputs, the rest inputs contribute to the reduction of the cost of risk with their effect in the downside risk in agriculture.

At the sample mean (see table 5), an increase in the use of seed input can contribute to the reduction of the variance of risk. Conversely, such an increased use of seed can possibly lead to an increase in the cost of downside risk. Evaluated at the sample mean, family labor and other inputs are variance increasing. On the other hand, these farm inputs also increase the welfare gain with the reduction of the downside risk. These all imply that different inputs can have a varied effect on the cost of risk from the variance and skewness components.

Table 5: Farm inputs evaluated at the sample mean

| Variables | Mean effect | Variance effect | Skewness effect |
|---|---|---|---|
| Seed | -0.391$^{***}$ (0.074) | -1.330$^{***}$(0.408) | -8.163$^{***}$(3.120) |
| Family labor | 0.158$^{***}$ (0.056) | 0.739$^{**}$ (0.308) | 5.783$^{**}$(2.359) |
| Other inputs | 0.264$^{***}$ (0.066) | 0.864$^{**}$ (0.363) | 6.046$^{**}$ (2.779) |

N =2724, $^{*}$ if p<0.10, $^{**}$ if p<0.05, $^{***}$ if p<0.01. The values in brackets represent standard errors.

We estimate the first order condition using the marginal effects of each input for each individual observation from equation (3) and (4). For the estimation, we use a three stage least squares (3SLS) procedure. We also checked the results of the Seemingly Unrelated Regression approach for the first-order condition for consistency, and the result remains the same. The coefficients of these functions are used to estimate the Arow-Pratt absolute risk aversion (AP) and downside risk aversion (DS) which then will be used to estimate the relative risk premium (RP). The Wald test for the three estimations rejected the null hypothesis of parameter equality across inputs.

Table 6: Risk parameters of major inputs

| Inputs | Seed | | Family labor | | Other inputs | |
|---|---|---|---|---|---|---|
| | Coeff. | Std. err | Coeff. | Std. err | Coeff. | Std. err |
| Constant | .008 | .005 | .125$^{***}$ | .002 | -.023$^{***}$ | .002 |
| Variance | .685$^{***}$ | .024 | -1.263$^{***}$ | .016 | .849$^{***}$ | .008 |
| Skewness | -.063$^{***}$ | .004 | .167$^{***}$ | .002 | -.074$^{***}$ | .000 |
| AP | 1.37 | | -2.52 | | 1.69 | |
| DS | -0.38 | | 1.00 | | -0.44 | |
| RP | 25.7% | | 12.2% | | 16.9% | |
| Chi2 test of parameters equality | 23533, p> $x^2$=.000 | | 24740, p> $x^2$=.000 | | 12493,p> $x^2$=.000 | |

Note: N= 2688, $^{*}$ refers to p < 0.10, $^{**}$ refers to p < 0.05, and $^{***}$refers to p < 0.01.

The negative values in the AP and DS with respect to family labor indicate that farmers seem “risk loving” with respect to family labor. This could be due to the availability of limited off-farm and non-farm employment opportunities and low wage rate for the available ones in rural Ethiopia. In smallholder agriculture, family labor constitutes the major share for agricultural production activities, and options for labor hiring are limited to certain periods of the production season (Barrett et al., 2008) Given the low level of opportunity cost family labor, farmers would likely to employ the available labor in spite of its low marginal contribution to farm productivity. Furthermore, inefficient and less developed factor markets might impede the flexibility in the allocation of resources and, this is likely to increase the cost of risk in agriculture.

Except for family labor, farmers are risk averse with respect to inputs used in the production process. They exhibit risk aversion behavior in terms of both absolute risk aversion (variability of the gross margin) and downside risk aversion (e.g. risks related to crop failure, bad harvest or price fall) (Chavas and Di Falco, 2012; Menezes et al., 1980). Farmers in Ethiopia, like any risk-averse farmers elsewhere in the world, are willing to cost some of their profit to avoid absolute and downward side risk. This is in line with the assumption that we made in developing the framework and previous empirical findings in Ethiopia (Chavas and Di Falco, 2012; Di Falco and Chavas, 2009) and the rest of the world(Groom et al., 2008; Kassie et al., 2015b).

The average sample relative risk premium (percent of the income that farms are willing to give up to mitigate risk) estimated from the empirical analysis is 18.27%[18] of the gross margin. Groom et al. (2008) have found the relative risk premium ranging from 6% to 20% of the income of farmers with respect to different production inputs in Cyprus. Kumbhakar and Tveterås (2003)also find a relative risk premium estimates of 16% of the income in the Norwegian salmon farmers. In our analysis, the rough estimate for the willingness to pay of farmers in order to avoid risk is 3864 *Birr*. This is an average inherent cost of risk for smallholder Ethiopian farmers, implying that the cost of risk is crucial in farm decision making.

### V. Farm diversification and the cost of risk

Table 7 presents the estimation results of farm diversification in the household level. Most of the coefficients that explain farm diversification in the simple Tobit model remain important when we control for unobserved heterogeneity in the IV Tobit model. The overall adequacy of the instrumental variable technique is good. The Wald test rejects the null hypothesis of no

[18] When calculating the sample relative risk premium, the observations with negative RRP has been neglected since they are not in line with the assumptions of risk aversion and risk neutrality.

endogeneity in the estimation using the cost of risk exposure at the household level. We employ rainfall pattern at the onset and on the growing season and the lagged risk premium measure as instrumental variables in this estimation. Both of the instrumental variables used in the estimation are statistically significant to explain the cost of risk. Furthermore, the test statistics (the Cragg-Donald F Value of 18.22) confirm the strength of our instruments for the estimation.

Table 7: Estimation results of farm diversification

| Models | 1). Tobit model | 2). IV Tobit model |
|---|---|---|
| Risk Premium (RP) | $-.063^{**}$(.032) | $-.621^{**}$(.279) |
| Diversification index lagged | $.179^{***}$(.032) | $.196^{***}$(.038) |
| Age of the household head | -.002 (.003) | -.002 (.003) |
| Education level | $-.028^{*}$(.014) | $-.029^{*}$(.016) |
| Landholding | $.047^{**}$(.023) | .028 (.028) |
| Land fragmentation | $-1.199^{***}$(.169) | $-.973^{***}$ (.225) |
| Slope index of land | .123 (.080) | .142 (.092) |
| Soil fertility index | -.029 (.065) | -.016 (.075) |
| Slope*fertility | -.010 (.012) | -.013 (.014) |
| Off/non-farm income | $.005^{*}$(.003) | $.007^{**}$(.003) |
| Extension contact | .005 (.013) | .012 (.016) |
| Region_Amhara | .152 (.143) | $.327^{*}$(.187) |
| - Oromiya | $.783^{***}$(.146) | $1.081^{***}$(.218) |
| - South | $-378^{***}$(.143) | $-.287^{*}$ (.170) |
| Model adequacy | LR chi2 = 274.94 | wald-ch2=244.9, p>chi2=.000 |
| | Loglikel.=-1349.6 | wald test of exog. chi2 =5.4 Prob > chi2=.067 |

Note: B=953, $^{*}$ refers to $p < 0.10$, $^{**}$ refers to $p < 0.05$, and $^{***}$ refers to $p < 0.01$. The values in brackets represent standard errors.

Table 6 illustrates the implication of the cost of risk exposure (risk premium) on the diversification decision of the farm household. The result is consistent through the alternative methods of estimations. Nonetheless unobserved heterogeneity in the simple Tobit model suppress the effect of the cost of risk (-0.063) on diversification. This effect is more pronounced (-0.621) when we control for unobserved heterogeneity and we employ the IV Tobit method. This result is in line with both the theory in applied economics and empirical works. Bezabih and Sarr (2012) show that risk preferences of the farm household can influence crop diversification decision. Their work is based on risk preferences derived from an experiment. In this paper, we show that the cost of risk that farmers experience can eventually influence their farm management decision. In this way, our paper augments the work of Bezabih and Sarr (2012) as the risk perceptions of people are majorly influenced by the costs that people incur with uncertain events. Overall, the estimation result verifies that the cost of risk in the farm household is important element of the welfare (certainty equivalent) of the household, and it does influence the farm diversification decision of the household.

The effect from past diversification experience could partly be due to the irreversibility (or costly reversibility) of some investments, at least in a short run or the time lag that some adjustments require (Song et al., 2011). They show that irreversibility makes thing more complex to change land with perennial crops and trees to other arable land use systems. Farmers seem reluctant to change the existing production pattern, since they otherwise have to deal with higher level of uncertainties.

Some of the control variables used in the estimation significantly explain farm diversification. The diversification level of farms is different across different regions of the country. This could be due to variations in the agro-ecological and biodiversity, socio-economic and institutional conditions across different regions in Ethiopia. Education level of the farm household, off-farm income and the level of land fragmentation significantly explain some of the variability in the farm diversification. Despite the presence of some change in magnitude, these effects remain important in both of the estimation approaches. Table 7 shows that land fragmentation is significantly associated with farm diversification. Off-farm income is negatively associated with the farm diversification level of the household. This is in line with previous empirical findings on the possible trade-off between on-farm diversification and off-farm income (Finger and Sauer, 2014). Finger and Sauer (2014) for example, argue that farmers might choose either to diversify their farm or look for off-farm investment options as a response to occurrence of extreme events. Farms may stay specialized though risky, as far as the off-farm activities provide adequate buffer against extreme events. Farmers might also consider off-farm income, for instance from wage employment, as post shock adaptation mechanisms. Overall, engagement in off- and non-farm income and farm diversification could be seen as substituting strategies when it comes to agricultural risk mitigation. One has to be cautious when interpreting the issue of trade-off between farm diversification and off-farm activities, as we didn’t specifically control for the possible causality in this paper.

## VI. Conclusions and policy implications

This paper analyzes the implication of the cost of risk exposure on the farm diversification decision. Using a panel data of smallholder farmers from Ethiopia, we verified this hypothesis. First, we employ a moment based approach of a profit function with CRRA risk preferences to estimate the risk premium of farm households. Afterwards, we use an instrumental variable technique to investigate if the cost of risk exposure plays a significant role on the diversification decision of households after controlling for physical and regional, human capital, socio-economic and institutional aspects.

We found out that the cost of risk (risk premium) is an important proportion of the farm income in Ethiopia. Smallholders are averse to absolute risk and downside risk exposure, and we estimate a relative risk premium of 18.27%. The sample average willingness to pay for risk aversion estimate is around 3864 *Birr*. This can be translated as a rough estimate of farmer's willingness to pay to avoid absolute and downside risk. Exposure to risk in Ethiopia lead to a huge welfare loss in the last couple of decades, and this is reflected in a higher level of willingness to pay to mitigate risk.

We verified the research hypothesis that the cost of risk that the household experiences influence the farm diversification level. This implies that smallholder farm households in Ethiopia consider farm diversification as an ex-ante risk mitigation strategy. Farmers might sometimes prefer to engage in less risky and low return production activities, as risk might erode the welfare and lead to poverty. This is especially relevant in Ethiopia where the institutional and public readiness to serve as safety-nets at times of risk is low or underdeveloped. This is an important input for formulation of policy and strategies in the developing world. For instance, there have been efforts to promote specialization in smallholder agriculture to improve market orientation and productivity in agriculture. However, these efforts can't be fruitful, with limited and inadequate safety-net options. This is often expressed with the reluctance of farmers to shift to specialized farms. Interestingly, the choice of smallholder farmers seem justifiable when the issue of risk and related welfare loss comes in to consideration.

# 5. Social capital, income diversification, and climate change adaptation: Panel data evidence from rural Ethiopia

With David Wuepper and Johannes Sauer

**Abstract**

The choice between specialization and diversification of income is driven by multiple, interacting factors, such as economies of scale and scope, risk considerations, context, and household characteristics and contexts. Using panel data from Ethiopia, we investigate the role of social capital and the covariate risk of climate change and their interaction. We find that households with greater social capital tend to be more specialized, implying that diversification and informal insurance are substitutes in the mitigation of risk. We also find that this effect is significantly weaker in regions more prone to climate change, which is consistent with the average farmer being aware that informal insurance is not an effective protection against risks that affect the entire social network. We use instrumental variable random effects estimation to account for the plausible endogeneity of social capital and we also establish that our results do not depend on the poorest and most constrained individuals in our sample.

**Key words**: diversification; social capital; adaptive capacity; Ethiopia; climate change

**JEL Classifications: Q12; O13; D22; D24**

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## I. Introduction

There is a large theoretical and empirical literature on the determinants of income diversification (Barrett et al., 2001; Chavas and Di Falco, 2012; Ellis, 2000). Barrett et al. (2001) classify potential explanations for the degree of diversification as “push factors”, such as the attempt to reduce the income risk, and “pull factors”, such as economies of scope. The risk reducing potential of diversification applies when risks are not fully correlated, such that a failure in one activity can be partially compensated by the performance of others. Economies of scope (EOS) describe a reduction in average production cost from an increase in the range of activities undertaken (diversification). In contrast, economies of scale describe a situation where an increase in the scale any one activity reduces average production costs. Generally, EOS favour diversification while economies of scale encourage specialization, whereas risk mitigation usually favours diversification. Block and Webb (2001) investigate farmers in famine prone areas of Ethiopia and find that more diversified households have higher incomes, which is consistent with a risk mitigating effect of diversification. Jackson and Collier (1988), Liedholm and Kilby (1989); Walker and Ryan (1990) on the other hand, all find that diversification is linked to lower risk and lower incomes, and Katchova (2005) finds that diversification leads to lower risk and lower farm values in the US, which she calls the “diversification discount”.

Chavas and Di Falco (2012) investigate the role of risk reduction and EOS in Ethiopia and find incentives for both diversification and specialization, with the former dominating overall, due both to EOS and risk considerations. Dercon and Krishnan (1996) argue that risk considerations are less important for diversification choices than entry constraints. On the other hand, Bezabih and Sarr (2012) find rainfall shocks as an important determinants of diversification decision in Ethiopia. Similarly, Paul et al. (2016) show that Ethiopia’s farmers use diversification as a climate change adaptation strategy.

Climate change is a serious threat to Ethiopian agriculture (Deressa et al., 2009; Dinar et al., 2012; Kassie et al., 2015a). How serious depends in part on farmers’ choices (Adger et al., 2013; Lemos et al., 2013; Smit and Wandel, 2006). Di Falco et al. (2011) find, adaptation through technology adoption can reduce adverse climate impacts. Common climate change adaptation strategies relevant to Ethiopia are tree planting, soil bunds, cultivation of hedges, contour ploughing, irrigation, and water harvesting (Di Falco and Bulte, 2013). Income diversification is also a popular risk mitigation activity in Ethiopia and other parts of the developing world (Chavas and Di Falco, 2012; Di Falco and Chavas, 2009; Ellis, 2000; Lanjouw and Lanjouw, 2001). Adaptation to all climate and weather related risk has always been highly relevant in Ethiopia, where environmental shocks cause substantial impediments to escaping poverty (Barrett et al., 2001; Dercon, 2004; Dercon and Krishnan, 2000). Despite this, the adoption of risk mitigation instruments remains incomplete. Explanations for this include: lower initial income (Abdulai and CroleRees, 2001; Reardon et al., 1992; Shively, 2001), human and other capital constraints (Abdulai and CroleRees, 2001; Benin et al., 2004), imperfect factor and product markets (Gebremedhin and Swinton, 2003; Pender and

Fafchamps, 2006) and limited off- and non-farm opportunities (Abdulai and CroleRees, 2001; Bezu and Holden, 2014; Lanjouw and Lanjouw, 2001). Whether farmers are willing and able to adopt risk-mitigating technologies depends on standard economic arguments, such as financial means and information, but also on psychological and cultural factors, such as perceived self-efficacy and social capital (Di Falco, 2014; Di Falco and Bulte, 2013; Gebrehiwot and van der Veen, 2015; Wuepper et al., 2016).

Recently, attempts have been made to investigate the role of social capital for (non- and dis-) adoption of risk mitigation instruments (Di Falco and Bulte, 2013; Paul et al., 2016; Wossen et al., 2015). Di Falco and Bulte (2013) analyze the effect of socio-cultural sharing norms (a form of social capital) in Ethiopia on the adoption of risk mitigation activities (soil and water conserving technologies). They find that compulsory risk sharing attenuates the incentive to adopt such innovations. Paul et al. (2016) study the effect of social capital (measured as interpersonal trust) on collective and individual adaptation to climate change. They find that social capital increases contributions to collective adaptation measures but it also decreases private adaptation measures. Wossen et al. (2015) report the existence of possible interactions between various dimensions of social capital and the risk aversion of Ethiopian households in the process of technology adoption.

Most agricultural insurance in Ethiopia is informal and network based (Dercon et al., 2006; Mobarak and Rosenzweig, 2013; Wossen et al., 2016). As Wossen et al. (2016) find, social capital is an effective protection against idiosyncratic shocks, even though it is far from complete. However, social capital is ineffective when it comes to covariate risks,[19] especially when social capital is limited to the same community that is affected with risk. The two most prominent covariate risks in Ethiopia are weather and market related. In this study, we focus on the relationship between social capital as informal insurance, climate change as covariate risk, and income diversification as individual risk mitigation.

A research gap is the consideration of income diversification as a risk-mitigation tool and the role of social capital. Ethiopia’s farmers might specialize in production if they know that the implied risk is shared with network members. On the other hand, this strategy is not likely to be effective in mitigating covariate risk, such as climate change, which affects the entire social network. Normatively, farmers should specialize more if this increases their profits and if they

[19] Idiosyncratic risks are defined as those only affecting individuals and covariate risks are those affecting a significant share of individuals in a given place.

have sufficient social capital as an emergency insurance. However, the more they are exposed to climate change, the less they should rely on social capital as an insurance. We investigate whether this is a good description of actual farmer behavior using the two latest available rounds (2004 and 2009) of a publicly accessible panel data set from Ethiopia. Our analysis consist of two parts. First, we estimate the effect of social capital on specialization, testing the hypothesis that social capital enables greater specialization. Second, we re-estimate the effect of social capital on specialization in regions of Ethiopia with greater and less climatic change, respectively. Here we test the hypothesis that the specialization effect of social capital is greater in regions with a less climatic risk and smaller in regions with greater climatic risk.

## II. Empirical strategy

In this section, we first explain our approach (2.1.) and then how it helps us to identify the causal effect of social capital (2.2.).

### Fundamental Approach

In order to investigate the relationship between diversification and a farmer's social capital, we consider a farm household model with the following relationship:

$$D_{it} = f(X_{it}, L_{it}, S_{it}) + e_{it} \tag{1}$$

where $D_{it}$ is the level of diversification of household $i$ at time $t$, $X_{it}$ is a vector of household socio-economic variables, $L_{it}$ is a vector of farm characteristics, $S_{it}$ captures the social capital of the farm household, and $e_{it}$ is the household and time specific random error term.

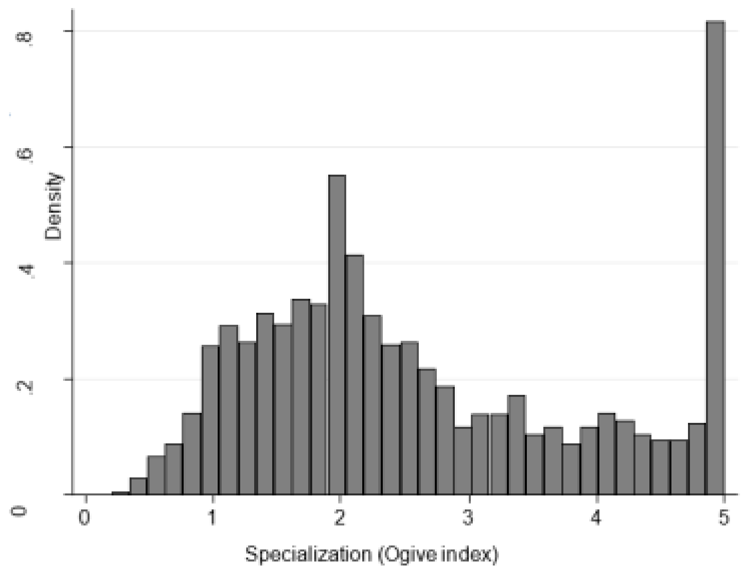
There are a number of measurement and econometric challenges to this empirical estimation. First, both the degree of farm specialization and social capital are not trivial to measure. For the former, we use the Ogive index proposed by Ali et al. (1991) and, as a robustness-check, alternatively the Herfindahl-Hirschman index (Rhoades, 1993), developed by Herfindahl (1950) and Hirschman (1964). The Ogive and Herfindahl-Hirschman indices both capture the number of activities and their contribution to the total income of the farm household. Our indices include income from cereal production, pulse and oil crops production, horticultural crops production, agro-forestry and forestry production, livestock production and off- and non-farm production activities.

These indices are given by:

$$OI = \sum_{n=1}^{N} \frac{\left(x_n - (1/_N)\right)^2}{1/_N} \quad \text{and} \qquad HI = \sum_{n=1}^{N} (x_n)^2 \tag{2}$$

where OI and HI respectively represent the Ogive and Herfindahl-Hirschman index, N is the total production activities and $X_n$ is the share of the income from production activities (cereal production, pulse and oil crops production, horticultural crops production, agro-forestry and forestry production, livestock production and off- and non-farm production activities). Both measures of diversification are continuous indices. Whereas the Ogive index lies between 0 (complete diversification) and 5 (full specialization), the Herfindahl-Hirschman index ranges between 0 (when is completely diversified) and 1 (specialization). Both measures are non-linear transformations of each other, and as will be seen below, both give the same result.

Figure 1. Income Diversification Distribution




Notes: The figure shows how specialized or diversified the sampled farmers are, between 0 (fully diversified) and 5 (fully specialized). Income sources are cereals, pulse and oil crops, horticultural crops, agro-forestry and forestry, livestock and off- and non-farm activities.

Figure 1 graphically depicts the density distribution between full diversification (Ogive index=0) and full specialization (Ogive index = 5). It can be seen that most farms are partially diversified. A few of the (almost) fully specialized farmers have particularly low incomes, even though the general association between specialization and income is slightly positive. This could mean that these households are highly specialized because of household or other constraints which oblige or force them to specialize. As we establish further below, our results remain robust when we exclude such farmers.

To capture the social capital of the farmers, the variables “Borrow“ (whether the head of the household believes that there is always someone that he/she can borrow 100 birr at hard times) and “Insurance” (whether the household is a member of at least one group-based funeral insurance scheme) are chosen, because they capture the defensive dimensions of social capital. “Borrow” captures the level of trust of the household head on the financial support that can be obtained from the social network during hard times. “Insurance” is the socio-cultural enforced protection for the household in hard times (such as sickness, fire and livestock loss, death of family members, etc.). As Dercon et al. (2006) highlight, group-based funeral insurance schemes give substantial protection to members at hard times. To “test” our selection, we also considered other indicators, such as a farmer’s social network, and we show in the empirical analysis that e.g. this variable is not amongst the important social capital dimensions when it comes to the decision of how much to specialize or diversify one’s income. Together, these variables capture how much the farmers expect to be helped when they need it. For our analysis, we develop a factor variable from these two variables using principal component analysis (see table 3). The literature on social capital and climate change adaptation suggests that the operationalization of social capital must be specific for each research question and context (Di Falco and Bulte, 2013). Another general pattern that emerges from the literature is that social capital generally helps groups of farmers to adapt to climate change though it also demotivates individual farmers to adopt costly adaptations. Furthermore, different dimensions of social capital have heterogeneous effects even on the same individuals. Hence, it is important to operationalize social capital in line with the relevant dimensions for the research question and context. As we are interested in the insurance-value of social capital, we choose indicators that reflect this dimension.

It should be noted, however, that neither of our social capital indicators is very restrictive. The survey question about borrowing money concerns a relatively small sum of money that many farmers can borrow and Iddir-membership is common in the survey areas. Thus, we identify the effects of social capital at the lower end of the spectrum, comparing a majority of farmers to those with relatively little social capital. By creating a factor variable from our two measures, we aim to capture more precisely the underlying, latent social capital than is possible with each measure alone. Another major concern in the estimation of this model is unobserved heterogeneity. Social capital could be endogenous in specification (1), e.g. if unobserved incentives and constraints correlate both with social capital and activity choices (Barr, 1998; Kozel and Parker, 2000; Narayan, 2002). If there is any economic value in social capital, it is quite plausible that there is a correlation with income and income-determinants. It is possible that higher income households have less incentive to join informal organizations and arrangements and it is similarly likely that higher income households are better able to join. More income often means more influence and this could lead to higher or lower trust in others. Furthermore, the ability to rely on others and borrow money in times of hardship might be positively associated with household income.

Because we are concerned about the endogeneity of our social capital variable, we use instruments: whether the spouse was born in the village; whether the father of the household head was/is an important person in the social life of the village; the historical coast distance of a farmer's ethnic group as sources of exogenous variation. Whether the spouse was born in the village is a credible instrumental variable because social capital requires time to develop and thus is often a function of how long the farmers live in their village (Di Falco and Bulte, 2013; Wossen et al., 2015). As Mariam (2003) finds, newly migrated households are less likely to be members of group based funeral insurance schemes, which can be seen as social capital indicator in Ethiopia. Whether the father of the household head was/is an important person in the social life of the village, reflects the fact that some social capital elements can be transferred through generations (Caeyers and Dercon, 2012; Gilligan and Hoddinott, 2007). The knowledge that a person acquires from parents is crucial to shape individual behavior, especially in the developing world where formal learning plays a smaller role. Furthermore, prestige might also be transferred vertically. As such, the social role of the parents affects the social capital of the farmers. The third instrument is based on the research by Nunn and Wantchekon (2011) who find a persistent long-term effect of the large slave trades in Africa on current levels of trust. Whereas Ethiopia has never been formally colonized by a European power, it was considerably affected by the slave trade (e.g. more than Ivory Coast, Kenya, or Mozambique, according to the data compiled by (Nunn, 2008)). Coast distance was a strong determinant of slave trade intensity (due to transaction costs) and has withstood a credible instrumental variable test with regard to trust by Nunn and Wantchekon (2011)[20].

Our instruments only help us to identify the causal effect of social capital if the parent's role in the community, farmer's birthplace, and farmer's ethnic origin only affect the production choices of the farmers through their social capital and not otherwise. As always, this exclusion

[20] As a falsification test, they tested whether the correlation between trust and coast distance can be found on other continents, that were unaffected by the large slave trades, i.e. Asia and Europe. It is found that the correlation between coast distance and trust only exists in Africa.

restriction is not directly testable but we argue is plausible, conditional on controlling for landholding, slope of the farm plot and fertility of soil, adequacy of rain and demographic parameters of the household. We estimate our model in an instrumental variables framework:

$$\begin{aligned} D_{it} &= f\left(X_{it}, L_{it}, \hat{S}_{it}\right) + v_{it} \\ S_{it} &= f(X_{it}, L_{it}, I_{it}) + u_{it} \end{aligned} \tag{3}$$

where $I_{it}$ is a vector of instrumental variables that are correlated with social capital but influence the diversification decision of the household only through the social capital, and $v_{it}$ and $u_{it}$ are random error components.

**Achieving identification**

Since we have panel data available, we can use random and fixed effects models, to take into account unobservable confounding variables. Our baseline regressions are represented by the following equation:

$$D_{it} = \beta_1 S_{it} + \beta_2 X_{it} + \beta_3 L_{it} + F_R + F_T + U_i + e_{it} \tag{4}$$

As mentioned above, we include fixed effects for regions ($F_R$) and time ($F_T$), which absorb unobserved variation between regions and years, in addition to a random effect $U_i$ which absorbs unobserved farmer characteristics. To move from correlations to causal effects, we instrument $S_{it}$ with three instrumental variables ($I_1 - I_3$), while we leave all other model parameters unchanged:

$$\begin{aligned} D_{it} &= \beta_1 S_{it} + \beta_2 X_{it} + \beta_3 L_{it} + F_R + F_T + U_i + v_{it} \\ S_{it} &= \alpha_1 I_1 + \alpha_2 I_2 + \alpha_3 I_3 + \alpha_4 X_{it} + \alpha_5 L_{it} + F_R + F_T + U_i + u_{it} \end{aligned} \tag{5}$$

As always, the instrumental variables must be strongly correlated with the endogenous variable, and they must meet the independence and exclusion restrictions[21]. In the previous section, we described the theoretical reasons why our instruments can be expected to be strong predictors of social capital. As statistical test, we always report the F-values for the excluded instrumental variables below the relevant (IV) results tables (Stock and M., 2005). At the end of the next section (3. Data), we explore the credibility of our instrumental variables by testing whether they correlate with a selection of our control variables. The test follows a similar logic as the test for omitted variable bias developed by Altonji et al. (2005). The more our instrumental variables correlate with other determinants of diversification, the higher the risk that

[21] Independence means the instrument is as good as randomly assigned. The exclusion restriction demands that the instrument affects the outcome only through the endogenous variable.

independence and exclusion restrictions are violated. We test whether our instrumental variables correlate with rainfall during the growing season, average slope of the fields, and market distance. While finding correlations do not indicate that the instruments necessarily violate their restrictions, they would indicate the likelihood.

Since we have three instrumental variables for one endogenous one, we can also employ the Sargan overidentification test. It should be noted that this test is neither necessary nor sufficient for the instruments to be valid (Deaton, 2010; Parente and Silva, 2012). However, it helps us to better understand the working of our instruments. If the Sargan overidentification test passes, this indicates that our three instrumental variables identify the causal effect of social capital for the same subpopulation in our sample (those who are affected by the instrumental variables). If the test fails, this means that either the exclusion restriction is violated, or the instrumental variables identify the causal effect of social capital for different subpopulations in our data (Angrist and Imbens, 1995). To test the hypothesis that the effect of social capital on income specialization might be different as a function of regional characteristics, we split our sample into two regions more and less affected by climate change and estimate the same specifications as before for each region:

$$\begin{aligned} D_{it} &= \beta_1 S_{it} + \beta_2 X_{it} + \beta_3 L_{it} + F_R + F_T + U_i + v_{it} \\ S_{it} &= \alpha_1 I_1 + \alpha_2 I_2 + \alpha_3 I_3 + \alpha_4 X_{it} + \alpha_5 L_{it} + F_R + F_T + U_i + u_{it} \end{aligned} \quad \text{if CC Severe} \qquad (6a)$$

$$\begin{aligned} D_{it} &= \beta_4 S_{it} + \beta_5 X_{it} + \beta_6 L_{it} + F_R + F_T + U_i + v_{it} \\ S_{it} &= \alpha_6 I_1 + \alpha_6 I_2 + \alpha_7 I_3 + \alpha_8 X_{it} + \alpha_9 L_{it} + F_R + F_T + U_i + u_{it} \end{aligned} \quad \text{if CC Moderate} \qquad (6b)$$

In the appendix, we show climate maps of Ethiopia on past climate change (figure A2) and future projections (figure A3). Based on these maps we divide the dataset into two groups, which differ by the salience of climate change in the regions. Our sample includes the regions Tigrai, Amhara, Oromia and the Southern Nations and Nationalities and Peoples Regions (see figure A2 in the on-line appendix). It can be seen that the north of Ethiopia (Tigrai) is more severely affected by climatic change than the center and south (Amhara, Oromia and the Southern Nations and Nationalities and Peoples Regions).

## III. Data

We use an unbalanced panel dataset of the International Food Policy Research Institute (IFPRI), the Center for the Study of African Economies (University of Oxford) and the Economics department of Addis Ababa University (Hoddinott and Yohannes, 2011). The data is from four major regions in Ethiopia (Tigrai, Amhara, Oromia and the Southern Nations and Nationalities and Peoples Regions). We use a total of 2653 observations from the 2004 and 2009 rounds (the two latest available rounds). The descriptive statistics of our key variables are presented in table 1, and across climate change regions in table 2.

Table 1. Variable list and sample descriptive statistics for 2004 and 2009

| Variables | 2004<br>Mean (SD) | 2009<br>Mean (SD) |
|---|---|---|
| AGE (Age of the household head in years) | 50.25(14.9) | 52.52(14.7) |
| EDUCATION (Years completed) | 1.21 (2.43) | 1.89 (2.88) |
| Ability to BORROW 100 birr when necessary (0=no, 1=yes) | 0.57 (0.49) | 0.75 (0.43) |
| Whether the household has funeral INSURANCE (0=no, 1=yes) | 0.79 (0.40) | 0.85 (0.36) |
| OUTSIDE NETWORK | 0.51 (1.13) | 0.39 (1.02) |
| LANDHOLDING in hectares | 1.07 (0.58) | 1.07 (0.63) |
| OGIVE INDEX (0=fully diversified, 5=specialized) | 2.98 (1.35) | 2.32 (1.19) |
| HERFINDAHL INDEX (HI) (0=fully diversified, 1=specialized) | 0.67 (0.22) | 0.56 (0.19) |
| SLOPE index (1=flat, 2=medium, 3=steep) | 1.29 (0.47) | 1.32 (0.63) |
| FERTILITY index (1=fertile, 2=medium, 3=infertile) | 1.61 (0.65) | 1.62 (0.82) |
| Adequacy of RAIN in the growing period (0=too little, 1=enough, 2=too much) | 0.82 (0.58) | 0.79 (0.59) |
| SPOUSE BORN IN THE VILLAGE (0=no, 1=yes) | 0.51 (0.50) | 0.51 (0.50) |
| FATHER IMPORTANT for social life of the village (0=no, 1=yes) | 0.67 (0.45) | 0.67 (0.45) |
| Distance to TOWN (in kilometers) | 8.51 (4.66) | 8.47 (4.64) |
| ETHNIC COAST DISTANCE (distance from each farmer's ethnic group's origin to the coast in 100 Km) | 4.69 (1.64) | 4.84 (1.54) |

Table 2: Mean comparison for Regions more and less prone to Climate Change

| Variable | Severe | Moderate | Difference (SE) |
|---|---|---|---|
| OGIVE INDEX | 2.943 | 2.495 | -0.448*** (0.053) |
| HERFINDAHL INDEX (HI) | 0.658 | 0.592 | -0.066*** (.009) |
| LANDHOLDING | 0.959 | 1.132 | 0.172*** (0.027) |
| SLOPE | 1.356 | 1.279 | -0.077*** (0.023) |
| FERTILITY | 1.753 | 1.511 | -0.242*** (0.031) |
| RAIN | 0.607 | 0.906 | 0.298*** (0.023) |
| TOWN | 9.645 | 7.822 | -1.823***(0.179) |

| | | | |
|---|---|---|---|
| BORROW | 0.564 | 0.721 | 0.157*** (0.018) |
| INSURANCE | 0.585 | 0.947 | 0.361*** (0.013) |
| OUTSIDE NETWORK | 0.368 | 0.483 | 0.115*** (0.043) |

Notes: *, ** and *** indicate statistical significance at 10%, 5% and 1% probability levels.

Our factor analysis of social capital (table 3) combines the two separate risk mitigation strategies considered here (borrowing and insurance). The uniqueness statistic measures the proportion of total variance which is unique to the specific variable, and not shared by the other. As described in the previous section, we can explore the probability that our instrumental variables fulfill the independence and exclusion restrictions by testing whether and how strong they correlate with some of our control variables

Table 3: Factor analysis for social capital

| Variable | SOCIAL CAPITAL | Uniqueness |
|---|---|---|
| BORROW | .782 | .389 |
| INSURANCE | .782 | .389 |
| Eigen value | 1.223 | |

Table 4. Test of Instrument 1 (Spouse born in same village)

| | (1)<br>RAIN | (2)<br>SLOPE | (3)<br>DISTANCE |
|---|---|---|---|
| SPOUSE | .0708 (.0605) | .00696 (.0196) | .0631 (.102) |
| R-sq | 0.05 | 0.05 | 0.61 |
| N | 2175 | 2197 | 2197 |

Notes: We control for region, year, age, and education. Stars indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table 5. Test of Instrument 2 (Father Important)

| | (1)<br>RAIN | (2)<br>SLOPE | (3)<br>DISTANCE |
|---|---|---|---|
| FATHER | -.0306 (.0701) | .0374 (.0296) | .0937 (.150) |
| R-sq | 0.05 | 0.05 | 0.62 |
| N | 2183 | 2206 | 2206 |

Notes: We control for region, year, age, and education. Stars indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table 6. Test of Instrument 3 (Ethnic Coast Distance)

| | (1)<br>RAIN | (2)<br>SLOPE | (3)<br>DISTANCE |
|---|---|---|---|
| ETHNIC COAST DISTANCE | -.0786$^{***}$(.0263) | -.00769 (.0160) | 1.215$^{***}$(.102) |
| R-sq | 0.05 | 0.04 | 0.67 |
| N | 2448 | 2471 | 2268 |

Notes: We control for region, year, age, and education. Stars indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Our first instrument (whether the spouse of a farmer comes from the village where the farm is currently located) could be related to the land allocated to the household (more distant village connections leading to more sloped fields that are harder to work, worse rainfall, or more remote in terms of distance to the next market/town. Table 4 shows that none of these variables are significantly correlated with this instrument. The second instrument (whether the farmers' father was or is important in the village) which might help farmers secure better fields (less sloped, more rain, less remote), is also substantially unrelated to land characteristics (Table 5). Our final instrument is the distance of each farmer's historical, ethnical homeland, reflecting the historical connections with the slave trade. This instrument is generated by a different mechanism than the other two instruments, which should make the estimation framework more robust(Murray, 2006). Nevertheless, this variable is especially at risk of correlation with one of our three falsification outcomes, rainfall, slopes, and distance to the next market or town. Table 6 indeed shows that both rainfall and remoteness correlate with our final instrument, which suggests that it is important to test whether our results are robust to using our instruments individually and to variation in the control variables, such as rainfall and market distance.

## IV. Results

We begin with an estimation of the relationship between social capital and specialization, and whether this relationship is different as a function of climatic change in the regions. We then test whether our results are sensitive to our way of measuring diversification and whether our results might be biased by plausible sources of unobserved heterogeneity.

**Social Capital, Income Specialization, and Climate Change Adaptation**

We begin with an analysis to test three indicators for social capital separately. Table 7 shows four specifications: 7a, random effects, with only the social capital indicators; 7b, adds a vector of control variables; 7c and 7d repeat specifications 7a and 7b using a fixed effects model.

Table 7: Effects of social capital on specialization (Ogive index, random and fixed effects

| Specification | 7a | 7b | 7c | 7d |
|---|---|---|---|---|
| Model | Random effect (RE) | | Fixed effect (FE) | |
| INSURANCE | .644$^{***}$ (.112) | .564$^{***}$ (.113) | .332$^{*}$ (.187) | .319$^{*}$ (.197) |
| BORROW | .379$^{***}$(.058) | .319$^{***}$(.060) | .286$^{***}$ (.090) | .255$^{***}$(.092) |
| OUTSIDE NETWORK | -.018 (.034) | -.027 (.025) | -.051 (.037) | -.058 (.038) |
| AGE | | -.002 (.002) | | -.013$^{**}$ (.006) |
| EDUCATION | | -.029$^{***}$ (.011) | | -.071$^{***}$ (.026) |
| LANDHOLDING | | -.061$^{***}$(.015) | | -.030 (.021) |
| SLOPE | | .342$^{***}$ (.058) | | .143 (.097) |
| FERTILITY | | -.153$^{***}$ (.045) | | -.029 (.071) |
| RAIN | | -.009 (.021) | | .008 (.009) |
| TOWN | | -.009 (.009) | | |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Region fixed effect | Yes | Yes | No | No |
| Observations | 2569 | 2308 | 2569 | 2509 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Despite the existence of systematic variation[22] among coefficients in the fixed effects and random effects estimations, Table 7 shows that both ability to borrow and funeral insurance significantly influence the specialization intensity of farms in our sample. On the other hand, the strength of network of the family outside the village is never statistically significant in any of our estimation approaches.

[22] The Hausman test (chi2= 6.35 and prob.>chi2 = 0.0957) between model (7a) and model (7c), and (chi2= 23.57 and prob.>chi2 = 0.0088) between model (7b) and model (7d) reveal the existence of systematic variation between the fixed and random effects estimations.

Table 8 shows the results of four specifications using the social capital factor (Table 3) in place of the separate social capital variables. Specifications 8a and 8b are random effects regressions, without (8a) and with controls (8b). In both these specifications, the social capital factor is associated with increased specialization. To take into account endogeneity, specifications 8c and 8d show the results of 2SLS random effect regressions, again with (8d) and without (8c) controls. The first stage results can be seen in the on-line Annex (table A2). Also in table A2 in the Annex we show that we get very high Craig Donald F values (above 100) and the Sargan over-identification test indicates that all our three instrumental variables identify the same causal effect of social capital and do not violate the exclusion restriction. In addition, we explore the consistency of the estimates by including our instruments stepwise. We also show these results in the on-line Annex, in table A3a and A3b. In line with the Sargan test, this alternative exercise also indicates that our three instrumental variables identify the same, causal effect of social capital on income specialization.

Table 8: Estimation of the determinants of specialization (using Ogive index)

| Specification | 8a | 8b | 8c | 8d |
|---|---|---|---|---|
| Model | RE | | IV RE | |
| SOCIAL CAPITAL | .243$^{***}$ (.033) | .210$^{***}$ (.037) | .679$^{***}$ (.225) | .552$^{**}$ (.276) |
| AGE | | .002 (.002) | | .002 (.002) |
| EDUCATION | | -.006 (.009) | | .004 (.014) |
| LANDHOLDING | | -.087$^{***}$ (.016) | | -.058$^{**}$(.026) |
| SLOPE | | .330$^{***}$ (.056) | | .310$^{***}$ (.061) |
| FERTILITY | | -.135$^{***}$(.045) | | -.137$^{***}$(.046) |
| RAIN | | -.008 (.016) | | -.012 (.014) |
| Year fixed effect | yes | Yes | yes | yes |
| Region fixed effect | yes | Yes | yes | yes |
| $R^2$ | 0.15 | 0.17 | 0.12 | 0.16 |
| observations | 2653 | 2301 | 2340 | 2301 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table 8 shows that the estimated effect of social capital increases in magnitude between the baseline regressions (8a and 8b) and the instrumental variable regressions (8c and 8d). This suggests that omitted variables and measurement error bias our baseline estimates downwards. Qualitatively, all our results indicate that social capital leads to more specialization.

Table 9: Determinants of specialization across climatic regions (using Ogive index)

| | Severe | | Moderate | |
|---|---|---|---|---|
| Specification | 9a | 9b | 9c | 9d |
| Model | IV random effects | | | |
| SOCIAL CAPITAL | .582$^{***}$ (.064) | .544$^{***}$ (.098) | 1.351$^{***}$(.342) | .789$^{**}$ (.358) |
| AGE | | -.002 (.004) | | .002 (.002) |
| EDUCATION | | -.036 (.028) | | .022 (.015) |
| LANDHOLDING | | -.003 (.030) | | -.084$^{***}$(.025) |
| SLOPE | | -.027 (.091) | | .523$^{***}$(.074) |
| FERTILITY | | .135 (.082) | | -.318$^{***}$(.055) |
| RAIN | | -.003 (.015) | | -.031 (.040) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| $R^2$ | 0.13 | 0.15 | 0.06 | 0.14 |
| observations | 804 | 766 | 1546 | 1526 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Next, we explore whether this pattern is mediated by the experience of climatic change (table 9), by separating the sample into two groups: those farmers located in areas more severely affected by climatic change; those located in areas less severely affected by climatic change. We find that social capital leads to higher specialization in both regions, but the magnitude of the effect differs. In regions more affected by climatic change, social capital has a weaker effect on specialization than in regions less affected. As can be seen in the on-line Annex table A2, in our split samples the Craig Donald F values remain sufficiently high (above 10) but the Sargan over-identification test fails, indicating that our identification approach works better in the full sample than in the split samples. Nevertheless, when we perform a Chow test (p=0.37), the result clearly indicates that the estimated effect of social capital is not the same across the regions and baseline RE specifications give similar result.

**Robustness checks**

A concern raised in the literature on diversification is the consistency of estimations across different measurement approaches. The results using the Herfindahl-Hirschman index (Table 10) are qualitatively similar to those using the Ogive index (table 8 and 9), as expected, since both indices indicate very similar ranges of diversification/specialization. Another concern is that diversification might be impractical for some farmers or in some localities. Some farmers, for instance, might not have the opportunity to diversify (e.g. non-farm employment opportunities in some remote areas, crop activities in pastoral farming systems etc.), or when some activities are not profitable to the farmer because of local constraints. Conversely, some farmers could be forced to diversify due to market imperfections and high transaction costs (e.g. for those in very remote areas). Our data do not show such a pattern and we get a range of values of different levels of diversification in every peasant association in the sample, suggesting that it is not local incentives and constraints that bias our results, but individual ones. We have also re-estimated our models on restricted subsamples, excluding the most remote farmers, living at least 18km from the nearest town (on-line appendix, table A5), and excluding the poorest farmers, with a gross margin of 1000 birr or less (on-line appendix, table A6). The results remain qualitatively similar to those estimated for the whole sample. So far, we have not explored the kind of specialization or diversification that are shaped by distinct degrees of social capital and severity of climate change. An in-depth analysis would go beyond the scope of this research but we briefly explore basic correlations between farm enterprises in the on-line appendix (table A7). We find that the differences are more pronounced between climatic regions than between farmers with above or below average social capital. The largest difference regarding social capital is observed for the combination of cereal production and non-farm income (farmers with below average social capital are less likely to have this combination). When we look at the distinct climatic regions, we find that the largest differences are for combinations with cereals, horticulture, pulses, and non-farm income. The largest differences of all concern the combinations cereals and horticulture (much less likely in regions of severe climatic change) and the combination of cereals and non-farm income (much more likely in regions of severe climatic change). In particular, given the potential importance of non-farm income, future research might usefully focus on the influence of local and regional contextual factors, in addition to the household and social network factors explored here.

## V. Discussion and conclusion

There is a long tradition in the social sciences to argue about how well poor farmers are adapted to their environments and their binding constraints. Schultz (1980) argued that poor farmers are generally well adapted and their low productivity mostly comes from external constraints. This is consistent with the recent empirical evidence, for example Suri (2011) from Kenya. Other research, however, also provided evidence that is inconsistent with the "poor but efficient" hypothesis (Duflo et al., 2011; Mullainathan, 2005; Wuepper et al., 2016). In addition to individual biases, social and cultural variables have also been found to explain empirical deviations from profit maximization (Adger et al., 2009; Di Falco and Bulte, 2013; Paul et al., 2016). Di Falco and Bulte (2013) for instance show how compulsory sharing norms reduce the incentive for individuals to adopt risk mitigation activities. They argue that when farmers do not adopt sufficient individual risk mitigation measures, the entire network may be too much affected by an adverse weather shock to be of much help for the individual farmers. They interpret their findings as evidence of the possibility of a lack of self-protection in the presence of obligatory risk sharing among kinship members, and hence that traditional sharing norms might hinder development. One possible risk mitigation strategy is income diversification (Chavas and Di Falco, 2012).

There are both incentives for and against specialization, and the effects on household income risk depend on the type of diversification. This paper analyzes the interactions between social capital, climate change and income diversification using panel data from Ethiopia. We find evidence that Ethiopian farmers use social capital and income diversification as substitutes in their risk management. In regions with a particularly high covariate risk of climate change, the substitution between social capital and income diversification is markedly weaker, which we interpret as implying that farmers understand that social capital is not a good protection for risks that affect the entire social network.

Our contribution investigates two sources of observed heterogeneity: Social capital and climate change (Adger et al., 2009; Wossen et al., 2015; Wossen et al., 2016). Closely related to our research, Paul et al. (2016) find a positive association between social capital and the capacity to collectively deal with climate change adaptation and a negative association between social capital and individual risk mitigating behaviors, such as income diversification. The data do not allow Paul et al. (2016) to interpret their findings as causal, which they clearly emphasize. Arguably, our data allows us to identify causality between social capital and risk mitigation behavior and we find that on average, farmers use informal insurance to deal with idiosyncratic risk and income diversification to deal with covariate risk. However, there are also farmers who seem to rely on informal insurance to deal with covariate risk, which has been found to be ineffective and potentially dangerous (Wossen et al., 2016). Currently, our available data do not allow us to identify the shares of farmers who behave approximately optimally and those who deviate markedly (e.g. due to a lack of information or a behavioral bias). Without knowing the individual returns to different degrees of specialization, we can only observe choices and infer the underlying mechanisms indirectly. However, policy recommendations may vary, as information and behavioral nudges would be recommended policies for farmers who fail to maximize their profits because they make inappropriate choices. On the other hand, improved credit and market access, as well as infrastructure improvement and similar policies would be recommended for farmers who behave optimally but who are constrained by these factors. Accordingly, we suggest future research, based on more complete data to capture these variations and to analyze more carefully the share of Ethiopian farmers imprisoned in a cultural poverty trap, in addition to the share making sub-optimal choices versus those making highly constrained optimal choices.

## VI. Annexes

Table A1: Determinants of specialization (Random Effects Tobit)

| | Full sample | Full sample | Severe CC | Moderate CC |
|---|---|---|---|---|
| BORROW | .277$^{***}$(.058) | .241$^{***}$(.064) | .379$^{***}$ (.109) | .206$^{***}$(.077) |
| INSURANCE | .665$^{***}$ (.112) | .606$^{***}$ (.120) | .227 (.167) | .645$^{***}$(.168) |
| OUTSIDE NETWORK | -.039 (.024) | -.042 (.026) | .026 (.053) | -.068$^{**}$ (.030) |
| AGE | | .002 (.002) | -.002 (.004) | .002 (.003) |
| EDUCATION | | -.006 (.012) | -.044 (.028) | .005 (.013) |
| LANDHOLDING | | -.091$^{***}$(.016) | -.029 (.040) | -.121$^{***}$(.018) |
| SLOPE | | .403$^{***}$(.060) | .018 (.098) | .603$^{***}$(.073) |
| FERTILITY | | -.158$^{***}$(.048) | .138 (.086) | -.371$^{***}$ (.054)) |
| RAIN | | -.011 (.015) | .005 (.015) | -.053 (.042) |
| TOWN | | -.004 (.010) | .054$^{***}$(.016) | -.022$^{**}$ (.009) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Region fixed effect | Yes | Yes | No | No |
| Observations | 2569 | 2125 | 654 | 1471 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A2: First-stages from 2SLS

| | Table 8,Spec. c | Table 8,Spec. d | Table 9,Spec. b | Table 9,Spec. d |
|---|---|---|---|---|
| ETHNIC COAST DIST | .042** (.021) | .045** (.022) | .338***(.028) | .061***(.017) |
| SPOUSE | .163*** (.022) | .115*** (.024) | .228***(.049) | .097***(.027) |
| FATHER | .197*** (.034) | .106*** (.037) | .158**(.080) | .079*(.043) |
| AGE | | .001 (.001) | .004 (.003) | .001 (.001) |
| EDUCATION | | -.022*** (.007) | -.039*(.021) | -.016**(.007) |
| LANDHOLDING | | -.072*** (.009) | -.121***(.029) | -.048***(.010) |
| SLOPE | | .072** (.034) | -.017 ( .071) | .076*(.039) |
| FERTILITY | | -.026 (.028) | .157***(.061) | -.040 (.031) |
| RAIN | | .008 (.008) | .017*(.010) | -.018 (.023) |
| F value instrument | 245.07 | 104.88 | 42.70 | 11.25 |
| Sargan | 3.08 (P =.21) | 2.09 (P=.35) | 13.65 (P= .00) | 24.59 (P=.00) |
| $R^2$ (1st) | 0.17 | 0.38 | 0.53 | 0.07 |

Notes: *, ** and *** indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A3a: Stepwise Inclusion of instruments Second Stage (using Ogive index)

| | Coeff. (Std.err) | Coeff. (Std.err) | Coeff. (Std.err) | Coeff. (Std.err) |
|---|---|---|---|---|
| SOCIAL CAPITAL | 1.139***(.407) | .676***(.237) | .679*** (.225) | .572**(.285) |
| AGE | | | | .002 (.002) |
| EDUCATION | | | | .004 (.014) |
| LANDHOLDING | | | | -.058** (.026) |
| SLOPE | | | | .310***(.061) |
| FERTILITY | | | | -.137***(.046) |
| RAIN | | | | -.011 (.014) |
| TOWN | | | | -.001 (.010) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Region fixed effect | Yes | Yes | Yes | Yes |
| $R^2$ | 0.04 | 0.05 | 0.18 | 0.23 |
| observations | 2576 | 2542 | 2542 | 2301 |

Notes: *, ** and *** indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A3b: Stepwise Inclusion of instruments First Stage (using Ogive index)

| | | | | |
|---|---|---|---|---|
| FATHER IMPORTANT | .179$^{***}$(.039) | .125$^{***}$(.023) | .127$^{**}$(.024) | .107$^{***}$(.038) |
| SPOUSE BORN IN VILL. | | .174$^{***}$(.037) | .175$^{***}$(.037) | .116$^{***}$(.024) |
| ETHNIC COAST DIST. | | | .055$^{**}$(.022) | .048$^{**}$(.025) |
| AGE | | | | .001 (.001) |
| EDUCATION | | | | -.022$^{***}$(.007) |
| LANDHOLDING | | | | -.071$^{***}$(.009) |
| SLOPE | | | | .071$^{**}$(.034) |
| FERTILITY | | | | -.026 (.028) |
| RAIN | | | | .008 (.009) |
| TOWN | | | | -.002 (.007) |
| F value instrument | 278.46 | 245.12 | 211.01 | 90.38 |
| Sargan | | 3.09(P=.08) | 3.08(P=.21) | 2.03 (P=.36) |
| $R^2$ | .09 | .12 | .12 | .16 |
| observations | 2371 | 2340 | 2340 | 2301 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A4: Estimation of the determinants of specialization (Herfindahl-Hirschman index)

| Specification | 10a | 10b | 10c | 10d |
|---|---|---|---|---|
| Model | IV RE | IV RE | IV RE | IV RE |
| Sample | Full | Full | Severe CC | Moderate CC |
| SOCIAL CAPITAL | .124$^{***}$ (.037) | .113$^{**}$ (.048) | .089$^{***}$ (.016) | .148$^{**}$ (.062) |
| Controls | none | full | full | full |
| Year fixed effect | yes | yes | yes | Yes |
| Region fixed effect | yes | yes | no | no |
| $R^2$ | 0.12 | 0.16 | 0.16 | 0.13 |
| observations | 2340 | 2301 | 766 | 1535 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A5: Excluding the most remote farmers

| Specification | 11a | 11b | 11a | 11b |
|---|---|---|---|---|
| Model | RE | IV RE | IV RE | IV RE |
| Sample | Full | Full | Severe CC | Moderate CC |
| SOCIAL CAPITAL | .032$^{***}$ (.005) | .083$^{*}$ (.049) | .093$^{***}$ (.020) | .138$^{**}$ (.060) |
| Controls | none | all | none | all |
| Year fixed effect | yes | yes | yes | yes |
| Region fixed effect | yes | yes | yes | yes |
| $R^2$ | 0.16 | 0.15 | 0.16 | 0.13 |
| observations | 2306 | 2023 | 565 | 1458 |

Notes: $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A6: Excluding the poorest farmers

| Specification | 12a | 12b | 12a | 12b |
|---|---|---|---|---|
| Model | RE | IV RE | IV RE | IV RE |
| Sample | Full | Full | Severe CC | Moderate CC |
| SOCIAL CAPITAL | .616$^{***}$ (.224) | .494$^{*}$ (.284) | .529$^{***}$ (.103) | .637$^{*}$ (.347) |
| Controls | none | all | none | all |
| Year fixed effect | yes | yes | yes | yes |
| Region fixed effect | yes | yes | yes | yes |
| $R^2$ | 0.13 | 0.16 | 0.15 | 0.15 |
| observations | 2335 | 2089 | 639 | 1450 |

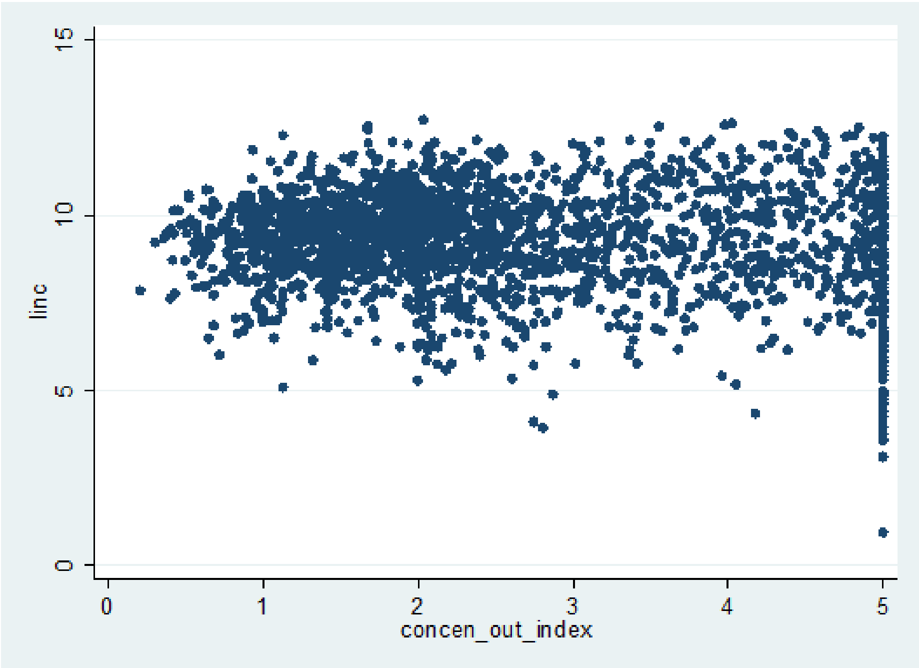
Notes: *, ** and *** indicate statistical significance at 10%, 5% and 1% probability levels. Standard errors are clustered by community.

Table A7: Correlations between Enterprises

| High Social Capital | | | | | | |
|---|---|---|---|---|---|---|
| | cereal | pulse | hort | forest | animals | non_farm |
| cereal | 1 | | | | | |
| pulse | -0.2913 | 1 | | | | |
| hort | -0.4170 | -0.2253 | 1 | | | |
| forest | -0.1386 | -0.0658 | -0.0726 | 1 | | |
| animals | -0.1945 | -0.1097 | -0.1270 | -0.0418 | 1 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| non_farm | -0.2379 | -0.1246 | -0.1413 | -0.0493 | -0.0261 | 1 |
| Low Social Capital | | | | | | |
| | cereal | pulse | hort | forest | animals | non_farm |
| cereal | 1 | | | | | |
| pulse | -0.3732 | 1 | | | | |
| hort | -0.3854 | -0.3136 | 1 | | | |
| forest | -0.1837 | -0.1236 | -0.0738 | 1 | | |
| animals | -0.1118 | -0.1303 | -0.0993 | -0.0484 | 1 | |
| non_farm | -0.0948 | -0.0704 | -0.0487 | -0.0284 | 0.0101 | 1 |
| More Severe Climate Change | | | | | | |
| | cereal | pulse | hort | forest | animals | non_farm |
| cereal | 1 | | | | | |
| pulse | -0.2911 | 1 | | | | |
| hort | -0.4315 | -0.3446 | 1 | | | |
| forest | -0.1697 | -0.1181 | -0.1118 | 1 | | |
| livestock | -0.0987 | -0.1097 | -0.1232 | -0.0481 | 1 | |
| non_farm | -0.0860 | -0.0653 | -0.0579 | -0.0308 | -0.0083 | 1 |
| Less Severe Climate Change | | | | | | |
| | cereal | pulse | hort | forest | animals | non_farm |
| cereal | 1 | | | | | |
| pulse | -0.4377 | 1 | | | | |
| hort | -0.2263 | -0.1506 | 1 | | | |
| forest | -0.0954 | -0.0390 | -0.0261 | 1 | | |
| livestock | -0.2662 | -0.1445 | -0.0638 | -0.0274 | 1 | |
| non_farm | -0.3392 | -0.1672 | -0.0879 | -0.0323 | -0.0324 | 1 |

Figure A1: The Correlation between Income and Diversification

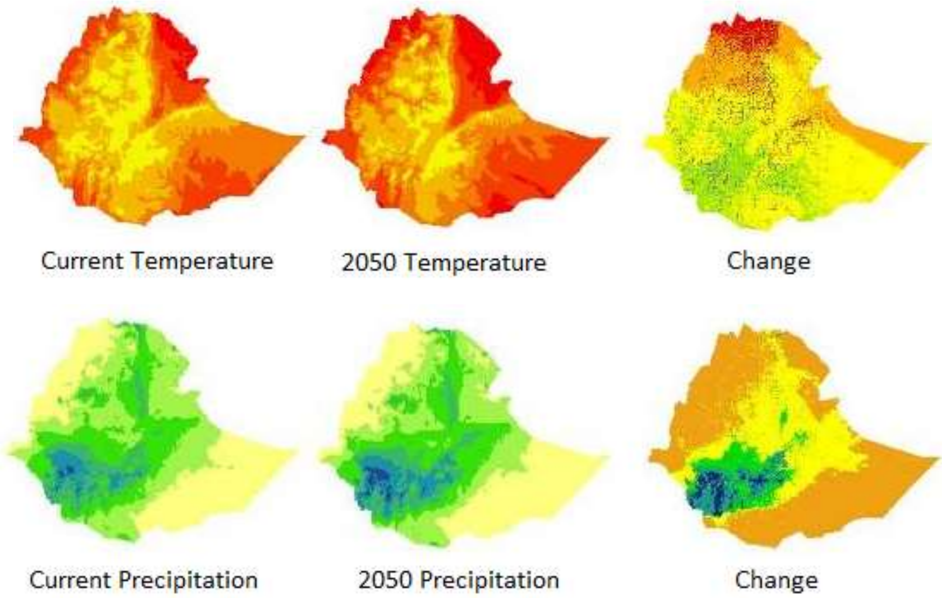



Notes: Y axis shows the natural log of income and the X axis shows the degree of income specialization, from full diversification (0) to full specialization (5). There is a slight positive relationship between specialization and income but also some negative outliers who are fully specialized.

Figure A2. Sampling Regions and Climatic Change


Notes: We computed this map by overlying the average precipitation and temperature in Ethiopia for the periods 2001 to 2010 and 2011 to 2015. Lighter areas had stronger climatic change than darker areas. The regions in all capitals are the sampling regions for our data. All climate data comes from the CRU (2017).

Figure A3: Climate change maps for Ethiopia




Notes: The upper three maps of Ethiopia respectively show the current temperature in the warmest quarter of the year (top left), a projection for 2050 (top middle), and the difference between the two (top right). From green (cold) to red (hot). The lower three maps show the current precipitation in the driest quarter of the year (bottom left), a projection for 2050 (bottom middle), and the difference between the two (bottom right). From blue (wet) to orange (dry). These figures have been created by Hopping and Wann (2016)

## 6. Risk exposure, climate variability, adaptation and farm disinvestment in Germany

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**Abstract**

This paper investigates the implication of the cost of risk exposure and climate variabilities on adaptation and input expenditure decisions in agriculture using a panel data of arable farms and weather variabilities from 1989 to 2009 from Germany. For this purpose, we develop a two stage empirical model. First, we estimate the profit moments function using the major inputs of production with quadratic function. Following this, we estimate the relationship between exposure to risk and climate variabilities and major responses of farmers (farm diversification, purchase of insurance and input expenditures) via GMM three-stage least squares (3SLS) approach. Our empirical analysis confirms that risk exposure measured with variance and skewness of farm profit can significantly influence the level of farm diversification, insurance policy purchase and farm input expenditure in arable farms. And this implies that improving the adaptive capacity of farms might not only secure them pervasive impacts of risk exposure, but also can influence their investment and disinvestment decisions. As the risk management strategies seem not to be completely substitutable, this evidence can be used to support the discussion of improving the availability and performance of market based instruments to strengthen the adaptive capacity of farms.

**Key words**: adaptation, climate change, disinvestment, risk
The content of this chapter is currently under peer-review with the Environmental and Resource Economics Journal.

### I. Introduction

It is a stylized fact that agriculture is inherently uncertain and this largely arise from climate variabilities (Intergovernmental Panel on Climate Change, 2007; OECD, 2009). Previous empirical studies and projections indicate that climate variabilities do significantly determine agricultural production (Ciais et al., 2005; Tubiello et al., 2000). As a response, agricultural sector has been in a continuous adjustment in order to cope with the ever changing environment (Baumgärtner and Quaas, 2010; Di Falco and Chavas, 2006; Hardaker et al., 2004; Zuo et al., 2014).

So as to reduce the pervasive effects of risk, farmers may invest in diversified economic activities. In this regard, probability of risk exposure, the severity of the hit and risk perceptions of the farm operator can play a vital role (Chavas, 2004). Bezabih and Sarr (2012) document that risk preferences and rainfall shock experiences do influence crop diversification decisions in Ethiopia. There are also some empirical evidences that document the impact of biodiversity in reducing the cost of risk in agriculture (Di Falco and Chavas, 2006, 2009). Despite the changing climate in Canada, Bradshaw et al. (2004) show that farmers are getting more specialized and the move to specialization is less likely to change in a short run. From utility maximization perspective, this implies that farmers specialize when the gain from specialization outweighs the gain from farm diversification. In risky production activity including agriculture, this is likely to occur when the market and institutions can offer other viable risk management schemes (e.g. insurance).

Insurance is among the widely used strategies to manage risk in agriculture. This is particularly true in the developed world (Enjolras and Kast, 2012; Enjolras and Sentis, 2011). Enjolras and Sentis (2011) argue that farmers with previous claims (risk experience) and larger farms have higher likelihood of purchasing insurance policies in France. They argue that insurance policies can sometimes be too expensive for smaller farms. Using data from Ethiopia, Duru (2016) indicated that farmers with public safety net experience fail to take up the follow up private insurance schemes. An empirical finding by Di Falco and Bulte (2013) in Ethiopia indicated that those with strong social networks are less likely adopt soil and water conservation schemes for risk mitigation. This implies that the presence of social safety net through social networks could give a disincentive for adoption of risk management strategies.

When the effects of shocks are detrimental to welfare, risk exposure can lead to negative investment (disinvestment). This could be associated with past shock experiences, expectation of probability and severity of shocks, and risk perception of the farm operator. For instance, Alem et al. (2010) show that past rainfall variability has detrimental effect on fertilizer application decisions for crop production in Ethiopia. Similarly, the work of Rijkers and Söderbom (2013) in Ethiopia indicated that negative shock in agriculture hampers investment in non-farm enterprises. According to them, the returns of non-farm business and agricultural production co-vary, and this limits the possibility of using non-farm activities for risk mitigation. Empirical paper from China documented that farmers are also likely to hold non-productive and precautionary liquid wealth in order to mitigate idiosyncratic shock (Jalan and Ravallion, 2001).

In an uncertain production setting, farm operators can either pick a risk mitigation strategy, or combination of a number of strategies (Hardaker et al., 2004; OECD, 2009). Similarly, risk can also influence (dis)investment decisions. Furthermore, farmers' adaptation strategies (e.g. farm diversification and (dis)investment responses can be interdependent. In this regard, De Mey et al. (2016) documented the existence of interrelationship between farm and off-farm risk mitigation strategies. This interrelationship can be either through their complementarity or through their competition for resources (Cafiero et al., 2007; De Mey et al., 2016; OECD, 2009). For instance, use of farm diversification as a risk management strategy is likely to influence the purchase of insurance policies. Similarly, farm diversification can also influence investment activities in the farm. Likewise, the nature of investment in agriculture can influence the adoption of risk management strategies (farm diversification or insurance). Nonetheless, there is no extensive empirical work that document the effect of risk exposure and climate variables on adaptation and input expenditure responses in the farm; and their interdependence.

The context of increasing threats from climate change on the one hand, and diverse farm level and market based responses of farms on the other, pose some empirical questions. How do farms respond to exposure to risk? Do these adaptation mechanisms and input expenditure responses interact with each other? These are questions that we try to address in this empirical paper. Understanding the cost of risk in agriculture, and farmers' adaptation and investment responses is crucial for development and policy. Of particular interest in this paper is to analyze the relationship between cost of risk exposure, climate variabilities, adaptation and farm input expenditure. Using a panel data of arable farms between 1989 and 2009 from Germany, we show that experience of risk exposure (measured with variance and skewness of the profit moments) and climate variabilities do influence crop diversification decision, purchase of insurance policy, and input expenditure of the farm. Furthermore, these farm and market based responses are interdependent.

## II. Empirical approach

In this paper, we analyze the impact of climate variabilities and risk exposure on farm diversification, purchase of insurance policy and input expenditure. Based on the approaches used in previous empirical literatures (Antle, 1983, 1987; Chavas and Di Falco, 2012), we use a moment based approach to calculate the first moment (mean), second moment (variance) and third moment (skewness) of farms. We start with a reduced form representation of a farm production output ($\pi_{it}$) function with respect to input vector ($X_{it}$).

$$\pi_{it}(z) = g(X_{it}) + u_{it} \quad (1)$$

Equation 1 in general is assumed to be stochastic in form, and the error term $u_{it} = \pi_{it} - g(X_{it})$ captures the production risk. The randomness of the distribution that often arise from climate variabilities, disease and pest outbreak, etc. is an important element to integrate risk component in the estimation. The second moment (the variance) and the third moment (skewness) of $u_{it}$ can be respectively represented as:

$$\hat{u}_{it^2}(z) = h_1(X_{it}) + v_{it} \quad (2a)$$

$$\hat{u}_{it^3}(z) = h_2(X_{it}) + e_{it} \quad (2b)$$

Equations (1), (2a) and (2b) are key for the empirical assessment for productivity and risk exposure (with risk premium[23]). The Arrow-Pratt relative risk aversion coefficient ($\alpha$), in empirical literature assumed to vary between 1 (mild risk aversion) to 4 (a more extreme level of risk aversion) is an essential component in risk premium estimation (Gollier, 2001).

For this particular analysis, we didn't assume a value for the risk aversion coefficient. We rather restrict ourselves to use the second moment (variance) and third empirical moment (skewness) as measures of the cost of risk exposure. This is particularly true under the assumption of general risk aversion and downside risk aversion, where an increase second moment (variance) and decrease third moment (skewness) increase the cost of risk exposure (Groom et al., 2008; Kim et al., 2014; Weitzman, 2009). Furthermore, it is vital to note that this coefficient is different across individual decision makers.

After we estimate the risk exposure, we investigate the impact of risk exposure and climate variabilities on farm diversification, purchase of insurance policy and input expenditures by controlling for demographic characteristics, environmental factors, Asset holding and subsidies, production structure etc. Building on the existing literature, we develop an empirical model that provide a framework to investigate this relationship. Farm diversification ($D_{it}$), purchase of insurance policy ($I_{it}$) and input expenditure ($E_{it}$) can be respectively expressed as a function of risk exposure, climate variabilities and other controls as:

[23] Under Constant Relative Risk Aversion (CRRA), the risk premium in (1) can be calculated from the mean, variance and skewness of the payoff distribution as: $R(z) = \frac{\alpha}{2}\frac{Var(\pi)}{E(\pi)} - \frac{\alpha(\alpha+1)}{6}\frac{Skew(\pi)}{[E(\pi)]^2}$, where, $\alpha$ represents the Arrow-Pratt relative risk aversion coefficient (Pratt, 1964), where $R_{var} = \frac{\alpha}{2}\frac{Var(\pi)}{E(\pi)}$ is the risk premium from the variance component and $R_{Skew} = -\frac{\alpha(\alpha+1)}{6}\frac{Skew(\pi)}{[E(\pi)]^2}$ is the risk premium from the skewness component (Chavas and Di Falco, 2012).

$$D_{it} = f_1\left(D_{i(t-1)}, R_{i(t-1)}, I_{it}, E_{it},\ C_{it}, S_{it}\ , L_{it}\right) + e_{1it} \tag{3a}$$

$$I_{it} = f_2\left(I_{i(t-1)}, R_{i(t-1)}, D_{it}, E_{it}, C_{it}, S_{it}\ , L_{it}\right) + e_{2it} \tag{3b}$$

$$E_{it} = f_3\left(E_{i(t-1)}, R_{i(t-1)}, D_{it}, I_{it}, C_{it}, S_{it}\ , L_{it}\right) + e_{3it} \tag{3c}$$

In equations (3a), (3b), and (3c), vector $R_{i(t-1)}$ captures the lagged value (t-1) of risk exposure measured with the variance and skewness estimates from (2a) and (2b). ($C_{\mathrm{it}}$), ($\mathrm{S_{it}}$) and ($\mathrm{L_{it}}$) respectively represent vector of climate variables, demographic and socio-economic characteristics, and land characteristics of farm i at any time t. Equations (3a), (3b) and (3c) are also constructed to measure the causal relationship between crop diversification, insurance and input expenditure in the farm. $D_{i(t-1)}$, $I_{i(t-1)}$ and $E_{i(t-1)}$ represent the lagged values of farm diversification, insurance purchase and input expenditure respectively. We include the mean and variances[24] of climate variables (sunshine hour, temperature and annual rainfall) and their lagged values.

There are some econometric challenges to estimate equations 1, (2a), (2b), (3a), (3b), and (3c). First, we need to determine the functional form of the profit moments estimations in equations 1, (2a), and (2b). Second, there could be the issue of unobserved heterogeneity across farms that could lead to biased coefficient estimates. An example could be the possible difference in the managerial abilities and skills of farmers, variability in suitability of farms, etc. In order to control for such an observed heterogeneity, the fixed effect panel data estimation can be used. And, a fixed effects approach may control the problem when this unobserved heterogeneity is time invariant. At times, this unobserved heterogeneity can be time variant. In this case, instrumental variable method can be helpful to control the problem (Greene, 2002). A key question in this type of estimation is finding instruments that are adequately correlated with the endogenous variable, and can only influence the dependent variable through the endogenous variable. In panel data, lagged values can be used as instruments (Arellano and Bond, 1991; Blundell and Bond, 1998; Roodman, 2009), and we employ this approach for 1, (2a), (2b), (3a), (3b), and (3c).

Third, estimation of equations (3a), (3b), and (3c) can also be problematic as the error terms in the respective equations might be correlated to each other. A farmer experiencing exogenous shock can make simultaneous decisions to engage in diversified farming, insurance policy

[24] Here, the variances of climate indicators are calculated using a formula, $V(C_{it}) = \frac{1}{n}\sum(C_{it} - \bar{C}_{it})^2$

purchase or may decide to disinvest. This simultaneous farm decision requires simultaneous estimation especially when the decisions, and hence the error terms of each estimation can be correlated to each other. For this, we estimate (3a), (3b), and (3c) using the system of three-stage least squares technique. 3SLS allows efficiency improvement in the GLS estimation as the model permits non-zero covariance between the error terms across these equations ($e_{1it}$, $e_{2it}$ , and $e_{3it}$). Furthermore, endogenous variables can be included as explanatory variables in the estimation. To generate consistent estimates that accounts for correlation of error terms across equations, we can use instrumental variable approach in 3SLS specification (Davidson and MacKinnon, 1993; Greene, 2002; Zellner and Theil, 1962). In this case, we use the lagged values of levels of farm diversification, purchase of insurance policy and input expenditure, and the differences as instruments in a GMM 3SLS specification. As robustness check, we estimate (3a), (3b), and (3c) using Seemingly Unrelated Regression (SUREG) (Zellner, 1962; Zellner and Theil, 1962).

Fourth, one should control for heteroscedasticity problem in the 3SLS as it can lead to inconsistent estimates. Following the approach suggested by Wooldridge (2010), we estimate these systems of equations using Generalized Method of Moments (GMM) approach with a weight matrix that uses explanatory variables as instruments.

## III. Data and summary statistics

For the analysis, we employ panel data of Farm Accountancy Data Network (FADN) of arable and mixed farms from Germany. This dataset comprises of arable farms[25] and weather data from 1989 to 2009. For the empirical analysis, we use 30503 observations. All the values related to the prices of farm products are deflated towards the base year 1989 by the national price index. In the same analogy, input costs and capital items are deflated with the input price index. The farm level information is linked with regional historical weather data from Deutscher Wetterdienst.

Table 1: Summary statistics of sample farms in Germany

| | Mean | Std. dev |
|---|---|---|
| Land (in hectares) | 197.74 | 427.22 |
| Seed cost (in Euros) | 10384.98 | 24344.89 |
| Labor (in hours) | 7441.696 | 17150.04 |

[25] This dataset is a subset of the FADN data from the EU which only comprises of arable and mixed farms in Germany.

| | | |
|---|---|---|
| Fertilizer cost (in Euros) | 16014.11 | 34495.68 |
| Crop protection (in Euros) | 15196.12 | 31548.42 |
| Energy (in Euros) | 15415.72 | 37263.88 |
| Asset (in Euros) | 705247.8 | 1015290 |
| Livestock (in TLU) | 63.05 | 231.54 |
| Livestock expenses (in Euros) | 252.81 | 894.57 |
| Gross income (in Euros) | 113756.6 | 252652.1 |
| Age of the manager (in years) | 48.02 | 17.24 |
| Sunshine hour | 1622.81 | 146.79 |
| Mean annual temperature | 9.27 | 0.76 |
| Mean annual precipitation | 816.68 | 165.40 |
| Crop diversification | | |
| - Crop count (count index) | 6.028 | 2.226 |
| - Crop count per hectare (count index) | 0.097 | 0.156 |
| - Herfindahl index | 0.270 | 0.155 |
| Total input expenditure (in Euros) | 290946.90 | 752331 |
| Insurance (in Euros) | 6156.25 | 12428.24 |

On average, farms in the sample are growing in size in the period between 1989 and 2009. There is also a similar trend on the input expenditures and insurance policies both in absolute terms and after we control for growth in size of operations. Farm diversification (measured with types of crops grown) seem to increase across years, between 1989 and 2009. However, there is no as such a clear trend in the number of crops grown per farm in Germany when we control for cultivated land. This is also confirmed when we measure farm diversification through Herfindahl index.

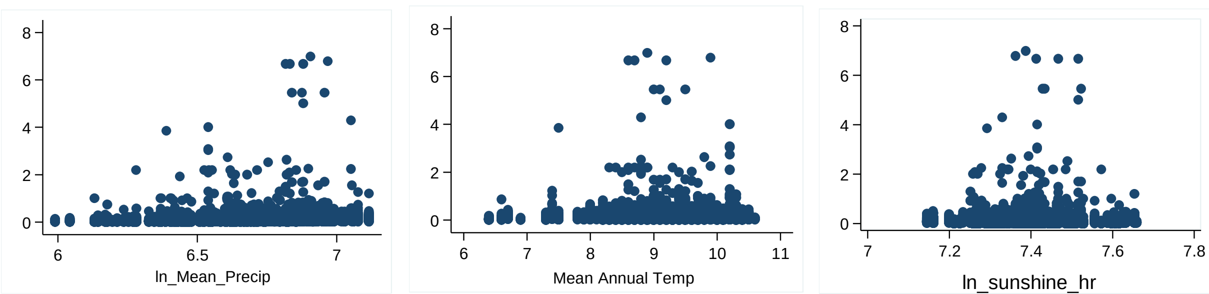


Figure 1a: Relationship between farm diversification, precipitation, temperature and sunshine

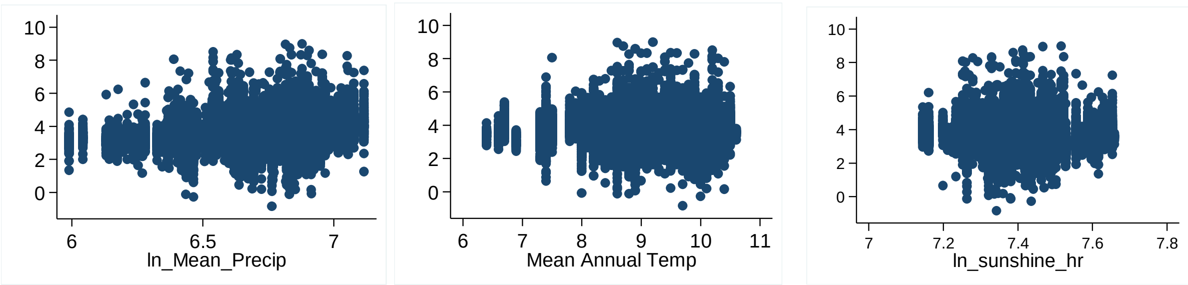


Figure 1b: Relationship between insurance, precipitation, temperature and sunshine

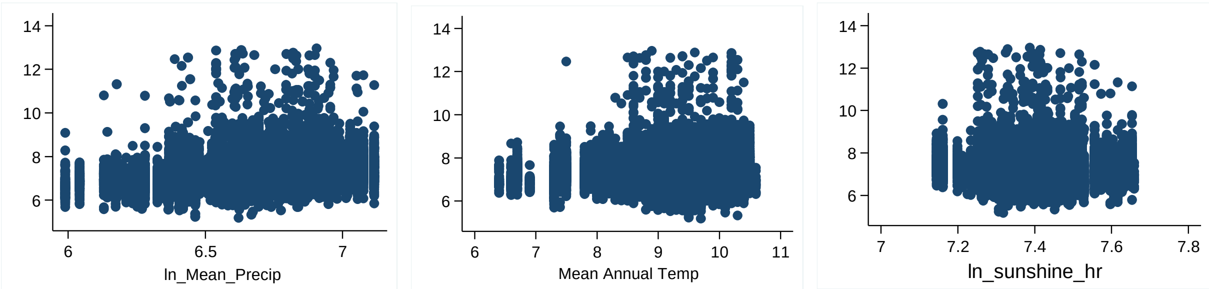


Figure 1c: Relationship between input expenditure, precipitation, temperature and sunshine

Figure (1a), (1b), and (1c) depict the development of crop diversification per hectare, purchase of insurance per hectare and input cost per hectare in sample farms with respect to climate variabilities in Germany. Overall, we can observe that weather variabilities are associated with the farm diversification, purchase of insurance and input expenditures. However, the strength of their associations varies across different weather effects. For instance, we can see a trend between precipitation and farm diversification (figure 1a). In the same way, we can observe stronger relationship between climate variabilities and insurance purchase (figure 1b). On the other hand, the relationship is weaker between climate variabilities and input expenditures (figure 1c).

Table 2 presents the correlation coefficients of climate variability indicators (annual precipitation, mean temperature and sunshine) with farm level adaptation and (dis)investment responses. The result confirms the relationship we observe in the graphs presented before (figure 1a, 1b and 1c). Both the correlation coefficients and the probability levels confirm that farms are more responsive to the changes in precipitation. Furthermore, the purchase of insurance is strongly associated with climate variability indicators. We will explore this in more detail in the following section.

Table 2: correlation between weather changes and crop count, insurance and input expenditure

| | Precipitation | temperature | Sunshine hour |
|---|---|---|---|
| Crop count | .164 (.000) | -.078 (.000) | .009 (.138) |
| Insurance | .093 (.000) | -.019 (.001) | .016 (.005) |
| Input expenditure | .034 (.000) | .010 (.073) | -.004 (.454) |

Note: Probabilities are presented in parenthesis.

**IV. Mean, variance and skewness estimation**

Based on the Akaike's Information Criterion (AIC) and Information Criterion (BIC), we choose the quadratic functional form for the profit moments functions against logarithmic specifications. We estimate the first moment (mean) using random effects (RE), fixed effects (FE) and instrumental variable random effects (IV RE) approaches. The estimation results of RE and FE models are presented in column 1 and 2 of Annex Table A2 respectively. The Du-Hauseman test in the first moment function (test statistic chi2= 20944.75 and p=0.000) verified the presence of systematic difference between the RE and FE coefficients. This indicates the existence of unobserved heterogeneity if we neglect to control the farm fixed effects. The fixed effect approach can control for unobserved heterogeneity if it is time invariant.

In order to control for this unobserved heterogeneity, we use instrumental variables through IV RE model. We use the lagged values of farm input values (land, labor, fertilizer, pesticide, energy and machine) as instruments. Both the individual values of the coefficients of the first stage estimation and the Cragg-Donald F-statistic of the overall model (F=708.7 with p=0.000) verifies that these variables are strong instruments, and can help to adequately identify the estimation. Table 3 present the first, second and third moments of the profit function (mean, variance and skewness respectively) that are estimated with IV RE model.

Table 3: Estimation of the second and third moment function (IV RE)

| | Mean | Variance | Skewness |
|---|---|---|---|
| Seed | .471$^{***}$(.018) | -.726$^{***}$(.042) | -3.304$^{***}$(.314) |
| Labor | .741$^{***}$(.013) | 1.722$^{***}$(.029) | 12.116$^{***}$(.225) |
| Fertilizer | -.038$^{***}$(.015) | .393$^{***}$(.034) | .906$^{***}$(.258) |
| Pesticide | .058$^{***}$(.005) | .019$^{***}$(.011) | .419$^{***}$(.082) |
| Energy | -.305$^{***}$(.027) | -1.312$^{***}$(.063) | -10.983$^{***}$(.481) |
| Machine | .109$^{***}$(.018) | -.618$^{***}$(.042) | -2.004$^{***}$(.316) |

| | | | |
|---|---|---|---|
| Seed^2 | -.016$^{***}$(.001) | .019$^{***}$(.001) | .063$^{***}$(.010) |
| Labor^2 | -.116$^{***}$(.002) | -.167$^{***}$(.004) | -1.607$^{***}$(.033) |
| Fertilizer^2 | .011$^{***}$(.001) | .048$^{***}$(.003) | .196$^{***}$(.026) |
| Pesticide^2 | -.007$^{***}$(.001) | -.006$^{***}$(.002) | -.034$^{***}$(.011) |
| Energy^2 | .125$^{***}$(.003) | -.070$^{***}$(.007) | -.706$^{***}$(.052) |
| Machine^2 | -.008$^{***}$(.002) | .012$^{**}$(.005) | -.306$^{***}$(.039) |
| Seed*Labor | .106$^{***}$(.001) | .093$^{***}$(.003) | 1.052$^{***}$(.026) |
| Seed*Fertilizer | -.044$^{***}$(.002) | -.164$^{***}$(.004) | -1.346$^{***}$(.030) |
| Seed*Pesticide | -.032$^{***}$(.002) | -.083$^{***}$(.004) | .739$^{***}$(.031) |
| Seed*Energy | -.135$^{***}$(.003) | -.058$^{***}$(.008) | -.249$^{***}$(.057) |
| Seed*Machine | .017$^{***}$(.003) | .217$^{***}$(.007) | .957$^{***}$(.054) |
| Labor*Fertilizer | .043$^{***}$(.002) | .152$^{***}$(.004) | 1.701$^{***}$(.030) |
| Labor*Pesticide | .009$^{***}$(.002) | -.046$^{***}$(.006) | -1.240$^{***}$(.042) |
| Labor*Energy | .098$^{***}$(.005) | .085$^{***}$(.012) | 1.618$^{***}$(.089) |
| Labor*Machine | .125$^{***}$(.003) | .085$^{***}$(.006) | .543$^{***}$(.048) |
| Fertilizer*Pesticide | .051$^{***}$(.002) | -.048$^{***}$(.005) | -.277$^{***}$(.036) |
| Fertilizer*Energy | .003 (.003) | -.078$^{***}$(.007) | 2.305$^{**}$(.064) |
| Fertilizer*Machine | -.057$^{***}$(.004) | -.161$^{***}$(.008) | -.468$^{***}$(.065) |
| Pesticide*Energy | -.113$^{***}$(.004) | .244$^{***}$(.009) | -.113$^{***}$(.004) |
| Pesticide*Machine | .024$^{***}$(.003) | -.072$^{***}$(.007) | .514$^{***}$(.049) |
| Energy*Machine | -.198$^{***}$(.005) | -.012 (.011) | -.446$^{***}$(.087) |
| Livestock | -9.9e-06 (8.2e-06) | 8.8e-06 (1.9e-05) | 3.3e-05 (1.4e-04) |
| Asset | 1.3e-08$^{***}$(1.9e-09) | 1.8e-08$^{***}$(4.4e-09) | 1.1e-07$^{***}$(3.3e-08) |
| Age of the manager | 7.7e-04$^{***}$(1.4e-04) | .002$^{***}$(3.3e-04) | .013$^{***}$(.002) |
| Region dummy | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes |

Note: ** and ***indicate significance levels at 5% and 1% probabilities. Standard errors are presented in parenthesis. Coefficients of regional and year dummies are not reported here to save space.

Most of the production inputs and explanatory variables significantly influence the first profit moment function in the expected direction. For instance, the coefficients of the levels of production inputs are positive, and their square terms are negative, except for fertilizer and energy use. This implies a non-linear first increasing and then decreasing function with respect to the major inputs of production.

Some of the inputs got a positive sign in the variance function, indicating that they do increase the variance in the farm income. Conversely, the negative sign of coefficients in the variance function indicate the contribution of these inputs towards reducing the cost of risk from the variance component. In the same way, a negative coefficient in the skewness function indicate an increase in the cost of risk through due to these inputs. A positive coefficient on the other hand reveal the contribution of these inputs towards reducing the cost of risk from the skewness component.

**V. The impact of climate variabilities and risk exposure on adaptation and (dis)investment**

Using the covariance analysis, we do find significant correlation for most of the relationships between cost of risk exposure captured by the variance and skewness of farm profit in the preceding production season with crop diversification, input cost and cultivated land in the sample farms (Annex Table A1). We start our analysis with simple and dynamic panel data regression assuming independence between adaptation and (dis)investment decisions.

Table 4 reports the relationship between risk exposure, climate variabilities and crop diversification[26]. In model (4a) and (4d), we respectively include the variance and skewness of the profit moments of previous year in RE and IV RE models. In order to control the dynamic nature, we include one year lag of the dependent variable. In (4b) and (4e), we respectively include climate variability indicators on the initial RE and IV RE models. Likewise, we build (4c) and (4f) with similar pattern by including all the other control variables using IV RE model.

In Table 5 & 6, we respectively report the impacts of risk exposure and climate variabilities on the purchase of insurance policies and input expenditures. For model building, similar procedure has been used as what is reported in Table 4.

[26] Using Herfindahl index for calculating crop diversification, we did the same estimation using RE model (see Appendix Table A3). The relationships and conclusions from the analysis we made using Herfindahl index remains the same with the rest of the estimations.

Table 4: Impact of risk exposure and climate variabilities on crop diversification (in crop count)

| | RE | | | IV RE | | |
|---|---|---|---|---|---|---|
| Model | 4a | 4b | 4c | 4d | 4e | 4f |
| Dep. var. (t-1) | .868***(.003) | .864***(.003) | .857***(.003) | .952***(.003) | .949***(.003) | .942***(.003) |
| Variance (t-1) | .008***(7e-04) | .008***(7e-04) | .009***(7e-04) | .009***(7e-04) | .009***(7e-04) | .009***(7e-04) |
| Skewness (t-1) | -7.6e-04***(9e-05) | -7.8e-04***(9e-05) | -8.1e-04***(9e-05) | -.001***(9e-05) | -.001***(9e-05) | -.001***(9e-05) |
| Sunshine | | -3.5e-06 (4e-06) | -3.7e-06 (4e-06) | | 1.0e-07 (4e-06) | 1.6e-06 (4e-06) |
| Temperature | | 1.6e-04 (.001) | 2.2e-04 (.001) | | -3.2e-04 (.001) | -6.2e-04 (.001) |
| Precipitation | | 1.4e-05*** (3e-06) | 1.2e-05***(4e-06) | | 1.3e-05***(3e-06) | 1.1e-05***(3e-06) |
| Sun_variance | | 2.3-04 (3e-04) | 2.6e-06 (3e-06) | | 2.1e-04 (3e-04) | 2.1e-04 (3e-04) |
| Temp_variance | | 9.36 (12.28) | 10.73 (12.28) | | 3.582 (12.08) | .245 (12.17) |
| Precip_variance | | -6.8e-04***(2e-04) | -6.5e-04***(2e-04) | | -6.1e-04***(2e-04) | -5.6e-04***(2e-04) |
| Insurance | 1.1e-04***(5e-06) | 1.1e-04***(5e-06) | 1.1e-04***(5e-06) | -2.2e-05***(5e-06) | -2.3e-05***(5e-06) | -2.9e-05***(6e-06) |
| Input expenditure | -4.8e-07***(6e-08) | -4.4e-07***(6e-08) | -6.2e-07***(7e-08) | 1.6e-07**(6e-08) | 1.9e-07***(6e-08) | 1.1e-07 (7e-08) |
| Asset (t-1) | | | 1.7e-07***(4e-08) | | | 2.5e-07***(3e-08) |
| Subsidy (t-1) | | | 1.1e-05***(3e-06) | | | -1.9e-06 (3e-06) |
| Livestock | | | -4.1e-06***(1e-06) | | | -1.1e-06 (1e-06) |
| Age manager | | | -5.4e-05**(3e-05) | | | -5.1e-05**(2e-05) |
| Less favored | | | 5.7e-04 (7e-04) | | | -1.9e-04 (6e-04) |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| Model summary | | | | F=206.9; P=0.000 | F=143.8; P=0.000 | F=197.7; P=0.000 |

Note: N=15749. $^{*}$, $^{**}$ and $^{***}$indicate significance levels at 10%, 5% and 1% probabilities. Robust standard errors are presented in parenthesis. Coefficients of regional and year dummies, and lagged climate variables are not reported here to save space.

Table 5: Impact of risk exposure and climate variabilities on insurance (in euros)

| | RE | | | IV RE | | |
|---|---|---|---|---|---|---|
| Model | 5a | 5b | 5c | 5d | 5e | 5f |
| Dep. var. (t-1) | .836$^{***}$(.003) | .833$^{***}$(.003) | .802$^{***}$(.003) | .836$^{***}$(.003) | .833$^{***}$(.003) | .802$^{***}$(.003) |
| Variance (t-1) | 31.82$^{***}$(.971) | 32.15$^{***}$(.971) | 30.00$^{***}$(.979) | 31.81$^{***}$(.971) | 32.15$^{***}$(.971) | 30.01$^{***}$(.979) |
| Skewness (t-1) | -4.018$^{***}$(.128) | -4.049$^{***}$(.128) | -3.817$^{***}$(.129) | -4.018$^{***}$(.128) | -4.049$^{***}$(.128) | -3.818$^{***}$(.129) |
| Sunshine | | .012$^{**}$(.005) | .015$^{***}$(.006) | | .012$^{**}$(.006) | .015$^{***}$(.006) |
| Temperature | | -2.127 (1.596) | -2.099 (1.585) | | -2.152 (1.596) | -2.120 (1.585) |
| Precipitation | | .009$^{*}$ (.005) | .009$^{*}$ (.005) | | .009$^{*}$ (.005) | .009$^{*}$ (.005) |
| Sun_variance | | -.416 (.423) | -.353 (.419) | | -.416 (.423) | -.358 (.419) |
| Temp_variance | | -454.5 (1736.2) | -976 (1729.0) | | -443.5 (1736.1) | -973.9 (1729.4) |
| Precip_variance | | -.117 (.294) | -.077 (.292) | | -.111 (.295) | -.075 (.293) |
| Diversification | -.829$^{***}$(.133) | -.784$^{***}$(.137) | -.514$^{***}$(.138) | -.834$^{***}$(.156) | -.781$^{***}$(.163) | -.448$^{***}$(.165) |
| Input expenditure | 4.3e-07 (4e-07) | 9.3e-07$^{**}$(4e-07) | 1.4e-06$^{**}$(6e-07) | 2.8e-07 (4e-07) | 7.7e-07$^{*}$ (4e-07) | 9.6e-07 (7e-07) |
| Asset (t-1) | | | 5.6e-04$^{***}$(4e-05) | | | 5.6e-04$^{***}$(4e-05) |
| Subsidy (t-1) | | | .022$^{***}$(.003) | | | .022$^{***}$(.003) |
| Livestock | | | -.002 (.002) | | | -8.2e-04 (.002) |
| Age manager | | | -.012 (.029) | | | -.012 (.029) |
| Less favored | | | -.829 (.721) | | | -.895 (.721) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| Model summary | | | | F=415.8; P=0.000 | F=192.6; P=0.000 | F=183.5; P=0.000 |

Note: N=15749. $^{*}$, $^{**}$ and $^{***}$indicate significance levels at 10%, 5% and 1% probabilities. Robust standard errors are presented in parenthesis. Coefficients of regional and year dummies, and lagged climate variables are not reported here to save space.

Table 6: Impact of risk exposure and climate variabilities on input expenditure (in euros)

| | RE | | | IV RE | | |
|---|---|---|---|---|---|---|
| Model | 6a | 6b | 6c | 6d | 6e | 6f |
| Dep. var. (t-1) | .984$^{***}$(.003) | .988$^{***}$(.003) | .969$^{***}$(.003) | 1.166$^{***}$(.004) | 1.173$^{***}$(.004) | 1.169$^{***}$(.004) |
| Variance (t-1) | -1018.6$^{***}$(35.33) | -1011.9$^{***}$(35.27) | -904.5$^{***}$(35.16) | -1024.9$^{***}$(38.57) | -1012.5$^{***}$(38.59) | -1007.4$^{***}$(39.21) |
| Skewness (t-1) | 122.87$^{***}$(4.14) | 122.67$^{***}$(4.14) | 109.91$^{***}$(4.13) | 122.35$^{***}$(4.87) | 120.31$^{***}$(4.88) | 120.09$^{***}$(4.94) |
| Sunshine | | -.417$^{**}$(.182) | -.542$^{***}$(.180) | | -.382$^{**}$(.200) | -.442$^{**}$(.201) |
| Temperature | | 14.05 (49.99) | 70.68 (49.51) | | -52.11 (57.56) | -65.13 (57.82) |
| Precipitation | | .209 (.161) | .188 (.160) | | .969$^{***}$(.184) | .889$^{***}$(.184) |
| Sun_variance | | -9.153 (12.94) | -3.634 (12.78) | | -22.54 (15.28) | -20.71 (15.31) |
| Temp_variance | | -176.7$^{***}$ (57.49) | 300.5$^{***}$(56.80) | | -149.62$^{**}$(62.65) | -148.70$^{***}$(63.05) |
| Precip_variance | | -4.917 (9.22) | -8.592 (9.114) | | -8.638 (10.624) | -6.981 (10.65) |
| Diversification | -3335.5$^{***}$(154.1) | -3457.0$^{***}$(154.9) | -3489.3$^{***}$(159.44) | -335.8$^{***}$(139.9) | -743.6$^{***}$(141.8) | -948.2$^{***}$(146.6) |
| Insurance | 3.374$^{***}$(.224) | 3.136$^{***}$(.223) | 4.039$^{***}$(.225) | -12.667$^{***}$(.282) | -12.938$^{***}$(.285) | -13.07$^{***}$(.300) |
| Asset (t-1) | | | -.002 (.002) | | | .008$^{***}$(.001) |
| Subsidy (t-1) | | | 2.657$^{***}$(.128) | | | .146 (.130) |
| Livestock | | | -.143$^{**}$(.064) | | | -.145$^{***}$(.049) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Age manager | | | -.166 (1.226) | | | -1.672 (1.049) |
| Less favored | | | -1.622 (31.97) | | | -92.72*** (26.18) |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| Model summary | | | | F=97.4; P=0.000 | F=96.3; P=0.000 | F=87.2; P=0.000 |

Note: N=15749. *, ** and *** indicate significance levels at 10%, 5% and 1% probabilities. Robust standard errors are presented in parenthesis. Coefficients of regional and year dummies, and lagged climate variables are not reported here to save space.

An increase in the variance of profit moments in the previous year is associated with the increased likelihood of crop diversification (Table 4) and purchase of insurance policy (Table 5) of farms. On the other hand, such an increase in the variance of profit moments lead to a decrease in the input expenditure in the following year (Table 6). In the same way, an increase in the skewness of the profit moment (decrease in the downside risk) in a farm is associated with a significant decrease on the level of crop diversification (Table 4) and purchase of insurance policy (Table 5) of farms in the following production season. Conversely, such a decrease in the downside risk is followed with a substantial increase the input expenditure (Table 6) of sample farms. Except little variations in the magnitude of the coefficients across RE and IV RE models, and without and with control variables, the relationships and conclusions remain consistent.

Table 4, 5 and 6 also report the effect of climate variabilities on crop diversification, purchase of insurance policies and input expenditures. A unit increase in annual precipitation is associated with a small marginal increase in the level of crop diversification of farms. We do find similar stories when we employ IV RE model to control unobserved heterogeneity, and without and with controls. This relationship remains (see Table 4). Sunshine hours in the year and annual precipitation appear to be important determinants of insurance purchase (Table 5). As reported in Table 6, sunshine hour in the year influences input expenditure in the farm with RE model. On the other hand, sunshine hours, annual precipitation and lag of sunshine hours appear to influence input expenditure with IV RE model. In Table 4, 5 and 6, we also report the interdependence between crop diversification, purchase of insurance policies, and input expenditure of farms. Alternative estimations in RE and IV RE models, and without and with control variables confirm the interdependence between risk management and investment decisions in the farm. Furthermore, some of the control variables significantly influence the farm diversification, insurance purchase and input expenditure decisions of farms in Germany.

In Table 7, we report empirical results of the impact of risk exposure and climate variabilities on crop diversification, insurance purchase and input expenditure using the General Method of Moments three-stage regression (GMM 3SLS) estimation technique. In models (7a), (7d) & (7g), we include the lagged variance and skewness variables in the estimations. Similarly, in (7b), (7e) and (7h), we include climate variability indicators on the initial model. In (7c), (7f) & 7i), we further include all the other controls. For robustness check, we estimate the relationship using seemingly unrelated regression (SUREG).

Table 7: Impacts of risk exposure and climate variabilities on crop diversification, insurance and input expenditure: GMM estimation 3SLS

| | crop diversification | | | Insurance | | | Input expenditure | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | 7a | 7b | 7c | 7d | 7e | 7f | 7g | 7h | 7i |
| Dep. var.(t-1) | .948*** | .947*** | .946*** | .878*** | .876*** | .869*** | 1.034*** | 1.038*** | 1.026*** |
| | (.003) | (.002) | (.003) | (.003) | (.003) | (.004) | (.003) | (.003) | (.003) |
| Variance(t-1) | .007*** | .007*** | .008*** | 25.14*** | 25.38*** | 25.91*** | -918.2*** | -913.37*** | -824.05*** |
| | (7e-04) | (7e-04) | (7e-04) | (.980) | (.980) | (.982) | (34.35) | (34.27) | (34.45) |
| Skewness | -7.1e-04*** | -7.2e-04*** | -7.6e-04*** | -3.345*** | -3.368*** | -3.453*** | 122.4*** | 121.48*** | 110.56*** |
| (t-1) | (9e-05) | (9e-05) | (9e-05) | (.129) | (.129) | (.129) | (4.33) | (4.32) | (4.34) |
| Sunshine | | -3.4e-06 | -3.9e-06 | | .009* | .009* | | -.373*** | -.365*** |
| | | (4e-06) | (4e-06) | | (.005) | (.005) | | (.173) | (.172) |
| Temperature | | -5.6e-04 | 1.1e-04 | | -1.765 | -1.301 | | 2.209 | 37.89 |
| | | (2e-05) | (.001) | | (1.595) | (1.585) | | (50.34) | (50.06) |
| Precipitation | | 8.2e-06** | 7.8e-06** | | .009* | .009* | | .495*** | .396** |
| | | (3e-06) | (3e-06) | | (.005) | (.005) | | (.162) | (.156) |
| Sun_variance | | 2.4e-06 | 2.6e-05 | | -.529 | -.449 | | -.375*** | -.369*** |
| | | (3e-06) | (3e-05) | | (.423) | (.419) | | (.158) | (.142) |
| Temp_variance | | 12.556 | 15.734 | | 480.5 | 115.4 | | -337.55 | -55.43 |
| | | (11.65) | (11.69) | | (1753.3) | (172.8) | | (553.3) | (49.59) |
| Precip_varianc | | -5.6e-05*** | -5.6e-05*** | | -.087 | .111 | | 9.185 | .161 |
| | | (2e-05) | (2e-05) | | (.295) | (.172) | | (9.38) | (.151) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Diversification | | | | -.636*** | -.689*** | -.616*** | -3137.2*** | -3347.5*** | -3304.10*** |
| | | | | (.119) | (.121) | (.125) | (110.88) | (112.78) | (115.93) |
| Insurance | 4.4e-05*** | 4.4e-05*** | 4.6e-05*** | | | | -.787*** | -.937*** | -.911*** |
| | (4e-06) | (4e-06) | (4e-06) | | | | (.191) | (.192) | (.196) |
| Input exp. | -5.7e-07*** | -5.6e-07*** | -6.0e-07*** | 1.2e-06*** | 1.5e-06*** | 1.7e-06*** | | | |
| | (5e-08) | (5e-08) | (6e-08) | (4e-07) | (4e-07) | (6e-07) | | | |
| Asset (t-1) | | | 3.1e-09 | | | 6.6e-04* | | | .004*** |
| | | | (3e-08) | | | (4e-05) | | | (.001) |
| Subsidy (t-1) | | | 7.6e-06*** | | | .025*** | | | 1.810*** |
| | | | (2e-06) | | | (.003) | | | (.113) |
| Livestock | | | -9.2e-07 | | | -.003 | | | -.173*** |
| | | | (9e-07) | | | (.002) | | | (.043) |
| Age manager | | | -5.5e-05*** | | | -.043 | | | -.893 |
| | | | (2e-05) | | | (.029) | | | (.917) |
| Less favored | | | -4.9e-05 | | | -1.039 | | | -29.01 |
| | | | (5e-04) | | | (.721) | | | (22.86) |

Note: N=15749. *, ** and ***indicate significance levels at 10%, 5% and 1% probabilities. Robust standard errors are presented in parenthesis. Coefficients of regional and year dummies, and lagged climate variables are not reported here to save space.

The results presented in Table 7 confirm that variances and skewness of profit moments in previous production season determine farm diversification, purchase of insurance policies and total input expenditures in farms.

An increase in the variance of profit moment in the previous period leads to an increase (β=0.007) in the level of farm diversification in the farm. And, this is consistent without controls (7a), when we include climate variables (7b) and when we include all other control variables (7c). Similarly, a decrease in the downside risk of profit moments in the previous season leads to decrease (β=-0.00071) in the level of farm diversification. There is very little variation in the magnitude of the coefficient when we include climate variability indicators (β=-0.00072) and all the control variables (β=-0.00075). In the same way, a higher variance and an increased downside risk in the previous year are associated with increased purchase of insurance policies. This is true with very little variation in magnitude of coefficients without controls (7d), when we control climate variables (7e) and with all the controls in the estimation (7f).

Table 7 also show that an increase in the variance of profit moments in the previous year leads to lower input expenditure (β=-918.2) in the farm. Similarly, a unit increase in the skewness of the profit moments (a decrease in the downside risk) in the previous season is associated with a substantial increase in the input expenditure (β=122.4) in the farm. These relationship and the follow-up concussions to persist, except a little change in the magnitude of the effect, with and without control variables.

In Table 7, we report the effect of climate variabilities on crop diversification, purchase of insurance policies and input expenditures. Unit changes in annual precipitation and the variance of annual precipitation are associated with marginal changes on crop diversification of farms (7b). There is only a small decrease in the magnitude of these effects when we control for other variables (7c). Similarly, an increase in annual sunshine hours and precipitation is associated with an increase in the purchase of insurance policy of farms (7e & 7f). Input expenditure of farms is significantly influenced by mean and variance of sunshine hours, and annual precipitation in the area.

Among the control variables, the amount of subsidy in the previous period and age of the manager do influence the intensity of crop diversification (7c). Similarly, asset holding and amount of subsidies in the previous period are associated with the purchase of insurance policy in the farm (7f). Lagged value of subsidy and asset holding and livestock ownership do influence the input expenditure of farms in Germany.

Table 7 also reports the existence of statistically significant interdependence between crop diversification, purchase of insurance policies and input expenditure of farms in Germany. For instance, we show that crop diversification reduces purchase of insurance policies and input expenditure (see 7d up to 7i). Similar relationship exist between crop diversification, insurance and input expenditure. This relationships confirm the likelihood of interdependence in risk management and investment decisions in farms in Germany.

Furthermore, we confirm this interdependence through significant relationship between the three models using SUREG. The Breusch-Pagan test of independence in the SUREG estimation with a chi2 value of 6423.28 and probability Pr= 0.000 when we only include variance and skewness of profit in the previous year, with a chi2= 6369.19 and a probability Pr= 0.000 when we further include climate variables, and with a chi2=6120.98 and a probability Pr= 0.000 when we control for other variables reject the null hypothesis stating zero correlation between the error terms of the three equations. This result verifies the interdependence between the major responses of arable farms for exposure to risk (i.e. farm diversification, purchase of insurance policies and input expenditure). The result from SUREG also confirm the consistency of the relationships between risk exposure, adaptation and investment (disinvestment) responses in sample farms in Germany. The conclusions made from the results of the IV GMM model and SUR model are similar, with only little difference in the magnitude of coefficients across these models (Annex Table A4).

## VI. Discussions and conclusions

Agriculture is inherently uncertain. Accordingly, understanding risk in agriculture and improving resilience of farms captured a significant attention from research and policy. There has been a continuous effort to document the impacts of climate variabilities and risk exposure on agriculture and livelihood. Such efforts also aim to understand farm operators’ adaptation and (dis)investment responses. This paper examines the effect of risk exposure and climate variabilities on crop diversification decisions, purchase of insurance policies and input expenditures using long panel data of arable farms from Germany.

Our analysis show that arable farms are likely to diversify their crop production activities as a response to higher profit variance and increased downside risk in the preceding years in sample farms in Germany. This implies that risk exposure of arable farms in the preceding years is associated with higher likelihood of diversifying farm activities. In an experimental study from Ethiopian farmers, Bezabih and Sarr (2012) show that risk averse farmers are more likely to engage in diversified farms. Such a choice towards diversified farm activities originate from the expected lower risk associated with it. With respect to this, Lin (2011) and Chavas and Di Falco (2012) document the role of farm diversification to as a buffer to environmental shock and to reduce the cost of risk.

When farm based risk mitigation instruments can't provide full protection against risk, farms in Germany can also invest in market based risk mitigation instruments. As presented in the result, the variance of the profit moments and downside risk in the previous year are associated with purchase of insurance policies. This implies that most farms in Germany are relying on both farm based (crop diversification) and market based (insurance) risk mitigation instruments in order to cope with risk. Furthermore, we show that crop diversification and purchase of insurance policies in Germany are interdependent with each other. The interdependence of these risk mitigation tools might reveal the incomplete protection of either of the risk mitigation schemes. With this evidence, we may question the existing belief on the complete substitutability of farm level and market based risk mitigation instruments.

This paper also show that farms that experience higher farm profit variability and downside risk in the preceding production year are likely to invest less expenses for farm inputs. Conversely, farms that experience positive shock in their profit (lower variance and lower downside risk) in the preceding production season are likely to invest more for input related expenses. This result confirms the research hypothesis that risk exposure is likely to determine the propensity to invest in the farm at least in a short run. In line with this result, Jalan and Ravallion (2001) indicated that wealth can be held unproductive in the presence of risk as a buffer against low income levels. A previous finding from Ethiopia by Rijkers and Söderbom (2013) document that such a negative shock in agriculture can also lead to negative investment in non-farm activities.

Climatic variables are essential elements of the farm adaptation, (dis)investment decisions in agriculture. We confirm that annual precipitation do significantly influence crop diversification, purchase of insurance and input expenditure decisions in Germany. Sunshine hours plays a vital role to determine insurance and input expenses. Similarly, mean annual temperature influences crop diversification decisions. This implies that climate variabilities do play an important role to shape adaptation and (dis)investment decisions in arable farms in Germany. There are similar findings on the impact of climatic variables on the level of farm diversification both in the developed and developing world (Bezabih and Sarr, 2012; Di Falco et al., 2010; Finger and

Sauer, 2014). Finger and Sauer (2014) for instance produced an evidence on the effect of the major climatic variables on farm diversification decisions in the UK. Bezabih and Sarr (2012) reported that farm diversification is strongly associated with rainfall variabilities in Ethiopia. Alem et al. (2010) found similar result on the impact of climate variabilities on fertilizer purchase decisions in Ethiopia. In addition to the direct effects of climate variabilities[27] on farm adaptation and (dis)investment responses, they also explain risk exposure and risk behavior in the farm.

In our empirical estimation, we show that post shock crop diversification decisions, purchase of insurance policies and farm input expenditure responses are substantially associated with each other. Farm diversification is one of the key strategies to manage risk. Diversified farms payoff especially when agricultural (or climate) risk has varied inter-crop effects (Lin, 2011). Nonetheless, farm diversification might not give complete protection against agricultural risk(Bradshaw et al., 2004; Cafiero et al., 2007). In this case, farms often look for market based risk management instruments (e.g. insurance). In most cases, farms consider multiple risk management strategies. To a certain extent, they can substitute with each other. However, they are not completely substitutable, and seem to coexist in German agriculture. Similarly, risk management and (dis)investment responses can be interdependent with each other. Crop diversification decisions and insurance purchases do substantially influence input expenditures and vice versa.

The findings in this paper can have several policy implications. First, we show that farm diversification and insurance are interdependent, and seem to work together in arable farms to mitigate the pervasive impacts of risk exposure. This might imply the incomplete protection of either of the risk mitigation schemes, and we question the existing belief on the complete substitutability of farm level and market based risk mitigation instruments. As these strategies seem not to be completely substitutable, this evidence can be used to support the discussion of improving the availability and performance of market based instruments to improve the adaptive capacity of farms. Second, negative shocks including a higher variance and downside risk are associated with negative investment (disinvestment) at least in a short run. Improving the adaptive capacity of farms might not only give protection from the pervasive impacts of risk exposure, but also can influence their investment and disinvestment behavior. Future research

[27] It is also vital to note that climate variabilities do substantially influence risk exposure (measured in the variance and skewness of the profit moments) in agriculture.

is suggested to explore the extent of substitution between different risk management strategies and other investment decisions in agriculture. Furthermore, incorporating the non-farm sector in the analysis can give a complete picture of risk balancing and investment decisions in German farms.

## VII. Annexes

Table A1: correlation between variance and skewness and farm response

| | Variance (t-1) | Skewness (t-1) |
|---|---|---|
| Crop count | .246 (.000) | .039 (.000) |
| Input cost | .406 (.000) | .153 (.000) |
| Cultivated land | -.014 (.079) | -.003 (.673) |

Note: Probabilities are presented in parenthesis.

Table A2: Estimation of the first moment function: Random effects, fixed effects and IV RE

| | Random effects | Fixed effects |
|---|---|---|
| Seed | .012 (.008) | -.095$^{***}$(.009) |
| Labor | .782$^{***}$(.009) | .480$^{***}$(.010) |
| Fertilizer | .035$^{***}$(.005) | .059$^{***}$(.005) |
| Pesticide | -.007$^{***}$(.002) | -.015$^{***}$(.002) |
| Energy | .159$^{***}$(.011) | .057$^{***}$(.013) |
| Machine | -.024$^{***}$(.006) | -.094$^{***}$(.005) |
| Seed^2 | -.002$^{***}$(2.2e-04) | .002$^{***}$(3.2e-04) |
| Labor^2 | -.049$^{***}$(.001) | -.053$^{***}$(.001) |
| Fertilizer^2 | .010$^{***}$(3.6e-04) | .001$^{***}$(5.2e-04) |
| Pesticide^2 | .002$^{***}$(3.7e-04) | .001$^{***}$(3.7e-04) |
| Energy^2 | .017$^{***}$(3.1e-04) | .004$^{***}$(5.2e-04) |
| Machine^2 | -.024$^{***}$(4.9e-04) | 5.6e-04$^{***}$(6.8e-04) |
| Seed*Labor | .041$^{***}$(5.9e-04) | .058$^{***}$(.001) |
| Seed*Fertilizer | -.004$^{***}$(3.2e-04) | -.006$^{***}$(5.9e-04) |
| Seed*Pesticide | -.026$^{***}$(4.6e-04) | -.007$^{***}$(8.2e-04) |
| Seed*Energy | -.004$^{***}$(3.7e-04) | -.034$^{***}$(6.9e-04) |
| Seed*Machine | 2.1e-04 (4.6e-04) | -.019$^{***}$(6.1e-04) |
| Labor*Fertilizer | 4.7e-04 (4.8e-04) | .014$^{***}$(9.0e-04) |
| Labor*Pesticide | .026$^{**}$(7.2e-04) | .001 (.001) |

| | | |
|---|---|---|
| Labor*Energy | -.029$^{***}$(7.8e-04) | .033$^{***}$(.001) |
| Labor*Machine | .067$^{***}$(.001) | .047$^{***}$(.001) |
| Fertilizer*Pesticide | .005$^{***}$(6.2e-04) | -.007$^{***}$(.001) |
| Fertilizer*Energy | -.029$^{***}$(4.9e-04) | -.026$^{***}$(8.2e-04) |
| Fertilizer*Machine | -.004$^{***}$(5.5e-04) | -.014$^{***}$(.001) |
| Pesticide*Energy | -5.4e-4 (5.9e-04) | .014$^{***}$(9.5e-04) |
| Pesticide*Machine | -.019$^{***}$(8.5e-04) | .016$^{***}$(.001) |
| Energy*Machine | .016$^{***}$(4.4e-04) | -.024$^{***}$(9.1e-04) |
| Livestock | -4.0e-06 (1.3e-05) | 1.3e-05 (1.5e-05) |
| Asset | 1.1e-08$^{***}$(3.1e-09) | 1.0e-08$^{***}$(3.5e-09) |
| Age of the manager | 3.1e-04$^{*}$(1.7e-04) | 3.2e-04$^{**}$(1.4e-04) |
| Region dummy | Yes | - |
| Year dummy | Yes | Yes |

Note: *, ** and ***indicate significance levels at 10%, 5% and 1% probabilities. Standard errors are presented in parenthesis. Coefficients of regional and year dummies are not reported here to save space.

Table A3: Impact of risk exposure and climate variabilities on crop diversification (in Herfindahl index)

| Model | RE | | | IV RE | | |
|---|---|---|---|---|---|---|
| | A3a | A3b | A3c | A3d | A3e | A3f |
| Dep. var. (t-1) | .794$^{***}$(.003) | .793$^{***}$(.005) | .803$^{***}$(.005) | .901$^{***}$(.005) | .896$^{***}$(.005) | .874$^{***}$(.005) |
| Variance (t-1) | -.002$^{***}$(1e-04) | -.002$^{***}$(1e-04) | -.002$^{***}$(1e-04) | -.002$^{***}$(1e-04) | -.002$^{***}$(1e-04) | -.003$^{***}$(1e-04) |
| Skewness (t-1) | 1.9e-04$^{***}$(1e-05) | 1.9e-04$^{***}$(1e-05) | 1.9e-04$^{***}$(1e-05) | 2.4e-04$^{***}$(2e-05) | 2.4e-04$^{***}$(2e-05) | 2.9e-04$^{***}$(2e-05) |
| Sunshine | | 2.4e-07 (6e-07) | 2.0e-07 (6e-07) | | 8.5e-07 (6e-07) | 1.4e-06$^{**}$(7e-07) |
| Temperature | | -2.5e-06 (2e-04) | -3.2e-05 (2e-04) | | -1.4e-04 (2e-04) | -2.9e-04$^{*}$(2e-04) |
| Precipitation | | 8.1e-07$^{**}$ (4e-07) | 7.2e-07$^{*}$(4e-07) | | 2.1e-06$^{***}$(6e-07) | 9.9e-07$^{*}$(5e-07) |
| Sun_variance | | 5.1e-04 (4e-05) | 4.9e-05 (4e-05) | | 3.4e-05 (5e-05) | 3.4e-05 (5e-05) |
| Temp_variance | | -2.324 (1.676) | -2.184 (1.685) | | -3.717$^{***}$(1.825) | -3.382$^{*}$(1.852) |
| Precip_variance | | -1.9e-05 (3e-05) | -1.5e-05 (3e-05) | | -1.7e-05 (3e-05) | 1.2e-05 (3e-05) |
| Insurance | -4.8e-07 (7e-07) | -7.1e-07 (7e-07) | -3.7e-07 (8e-07) | -2.6e-05$^{***}$(9e-07) | -2.8e-05$^{***}$(9e-07) | -3.7e-05$^{***}$(1e-06) |
| Input exp. | 3.3e-07$^{***}$(1e-08) | 3.3e-07$^{***}$(1e-08) | 3.3e-07$^{***}$ (1e-08) | 4.8e-07$^{***}$(1e-08) | 4.9e-07$^{***}$(1e-08) | 5.2e-07$^{***}$(1e-08) |
| Asset (t-1) | | | -1.3e-08$^{***}$(7e-09) | | | 1.4e-07$^{***}$(7e-09) |
| Subsidy (t-1) | | | -7.4e-07$^{*}$ (4e-06) | | | -4.9e-06$^{***}$(5e-07) |
| Livestock | | | -7.5e-07$^{***}$(3e-07) | | | -4.7e-06$^{*}$(2e-07) |
| Age manager | | | -1.3e-05$^{***}$(5e-06) | | | -8.0e-06$^{*}$(5e-06) |
| Less favored | | | -8.1e-05 (1e-04) | | | -9.9e-05 (1.3e-04) |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| Model summary | | | | F=104.8; P=0.000 | F=100.9; P=0.000 | F=74.47; P=0.000 |

Note: N=15749. $^{*}$, $^{**}$ and $^{***}$indicate significance levels at 10%, 5% and 1% probabilities. Robust standard errors are presented in parenthesis. Coefficients of regional and year dummies and lagged climate variables are not reported here to save space. A Herfindahl index close to Zero indicates complete diversification where as a value close to 1 refers to a specialized farm.

Table A4: Impacts of risk exposure and climate variabilities on crop diversification, insurance and input expenditure (pooled SUR model)

| | crop diversification | | | Insurance | | | Input expenditure | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | A4a | A4b | A4c | A4d | A4e | A4f | A4g | A4h | A4i |
| Dep. var.(t-1) | .944*** | .942*** | .936*** | .846*** | .844*** | .823*** | 1.069*** | 1.073*** | 1.060*** |
| | (.002) | (.002) | (.002) | (.003) | (.003) | (.004) | (.002) | (.002) | (.003) |
| Variance(t-1) | .011*** | .011*** | .011*** | 30.17*** | 30.48*** | 28.77*** | -756.0*** | -741.9*** | -721.4*** |
| | (7e-04) | (7e-04) | (7e-04) | (.980) | (.966) | (.976) | (33.44) | (33.37) | (33.54) |
| Skewness | -.001*** | -.001** | -.001*** | -3.852*** | -3.882*** | -3.708*** | 102.4*** | 100.6*** | 97.77*** |
| (t-1) | (9e-05) | (9e-05) | (9e-05) | (.128) | (.128) | (.129) | (4.27) | (4.27) | (4.28) |
| Sunshine | | -2.8e-06 | -1.9e-06 | | .011** | .013** | | .579*** | .299*** |
| | | (4e-06) | (4e-06) | | (.006) | (.006) | | (.073) | (.076) |
| Temperature | | -1.5e-04 | -1.2e-04 | | -1.956 | -1.882 | | -23.33 | -3.585 |
| | | (.001) | (.001) | | (1.594) | (1.583) | | (50.85) | (50.49) |
| Precipitation | | 9.8e-06*** | 7.9e-06** | | .009* | .009* | | .701*** | .582** |
| | | (3e-06) | (3e-06) | | (.005) | (.005) | | (.162) | (.161) |
| Sun_variance | | 2.8e-04 | 3.3e-04 | | -.448 | -.383 | | -13.278 | -8.491 |
| | | (3e-04) | (3e-04) | | (.422) | (.419) | | (13.49) | (13.377) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Temp_variance | | 9.245 | 8.528 | | -271.6 | -296.9 | | -911.11$^{*}$ | -24.40 |
| | | (11.63) | (11.66) | | (1733.9) | (1726.4) | | (553.2) | (49.71) |
| Precip_varianc | | -5.9e-04$^{***}$ | -5.6e-04$^{***}$ | | -.135 | -.078 | | -10.17 | -9.735 |
| | | (2e-04) | (2e-04) | | (.294) | (.292) | | (9.38) | (9.305) |
| Diversification | | | | -.619$^{***}$ | -.648$^{***}$ | -.591$^{***}$ | -2038.5$^{***}$ | -2265.6$^{***}$ | -2545.8$^{***}$ |
| | | | | (.112) | (.115) | (.119) | (93.93) | (95.50) | (100.2) |
| Insurance | 3.5e-05$^{***}$ | 3.5e-05$^{***}$ | 3.4e-05$^{***}$ | | | | -5.450$^{***}$ | -5.612$^{***}$ | -5.301$^{***}$ |
| | (4e-06) | (4e-06) | (4e-06) | | | | (.159) | (.161) | (.168) |
| Input exp. | -7.2e-07$^{***}$ | -6.9e-07$^{***}$ | -8.6e-07$^{***}$ | 1.2e-06$^{***}$ | | 1.3e-06$^{**}$ | | | |
| | (5e-08) | (5e-08) | (6e-08) | (3e-07) | | (6e-07) | | | |
| Asset (t-1) | | | 2.5e-07$^{***}$ | | | 4.1e-04$^{***}$ | | | .010$^{***}$ |
| | | | (3e-08) | | | (4e-05) | | | (.001) |
| Subsidy (t-1) | | | 7.2e-06$^{***}$ | | | .023$^{***}$ | | | 1.375$^{***}$ |
| | | | (2e-06) | | | (.003) | | | (.111) |
| Livestock | | | -8.6e-07 | | | -.002 | | | -.144$^{***}$ |
| | | | (9e-07) | | | (.002) | | | (.043) |
| Age manager | | | -3.8e-05$^{**}$ | | | -.021 | | | -.407 |
| | | | (2e-05) | | | (.029) | | | (.917) |
| Less favored | | | 2.1e-04 | | | -.915 | | | -42.36$^{*}$ |
| | | | (5e-04) | | | (.719) | | | (22.84) |

| | |
|---|---|
| Model summary | Breusch-Pagan test of independence for (A4a) (A4d) and (A4g): chi2(3) = 7341.09, Pr = 0.000 |
| | Breusch-Pagan test of independence for (A4b) (A4e) and (A4h): chi2(3) = 7329.01, Pr = 0.000 |
| | Breusch-Pagan test of independence for (A4b) (A4e) and (A4h): chi2(3) = 6791.53, Pr = 0.000 |

Note: N=15749. $^{*}$, $^{**}$ and $^{***}$indicate significance levels at 10%, 5% and 1% probabilities. Standard errors are presented in parenthesis. Coefficients of regional and year dummies are not reported here to save space.

# 7. Farm diversification, risk and productivity: Evidence from arable farms from Germany

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## Abstract

This paper analyzes the role of diversification and its effects on farm productivity and risk management. Using a panel data from a sample of arable farms in Germany over the period 1989 - 2009, we evaluate farm productivity and the cost of risk under alternative diversification schemes. The analysis relies on certainty equivalent welfare measures calculated from the mean, variance and skewness of a multi-output production function. We explore the role of farm diversification and its effects on productivity and risk management. The empirical analysis shows that diversification has significant effects of farm welfare through increasing productivity and reducing the cost of risk. It also documents how these effects vary across different diversification strategies.

**Keywords**: diversification, productivity, risk, specialization

**J.E.L.:** D24, D81, L25, Q12

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## I. Introduction

In response to technology and policy changes, farms in the European Union (EU) have gone through many structural changes over the last few decades (Chaplin et al., 2004; Jongeneel et al., 2008; Koundouri et al., 2009; Lansink et al., 2015; Zhu and Lansink, 2010). The number of farms has declined sharply, while the existing farms have increased in size (Bartolini and Viaggi, 2013; BMELV, 2006; Eurostat, 2013; Gollin and Probst, 2015). In the process, farms have gone through substantial changes in their structure of production and in their degree of output specialization (Jongeneel et al., 2008; Lansink et al., 2015; Meert et al., 2005). The evolving process of farm specialization or diversification has stimulated significant interest from researchers and policy makers.

Economists have examined the issue of economies of scale and efficiency gain from specialization. Starting with Smith (1776), economists have stressed the potential gains from specialization. Such arguments have stimulated empirical research evaluating the effects of farm specialization on farm productivity and efficiency (Lansink and Stefanou, 2001; Larson and Plessmann, 2009; Latruffe et al., 2005). Yet, complete output specialization is rare and most farms exhibit some form of output diversification. In Germany for instance, nearly 80% of the farm households get their income from at least two production activities(OECD, 2007). This indicates that there are benefits from diversification. Arguments have been made that more diversified systems can reduce risk exposure, improve farm resilience and enhance adaptation to climatic and market shocks (Di Falco and Chavas, 2006, 2009; Lin, 2011; Meert et al., 2005). Complementarity among outputs and jointness in their production can also generate productivity gains in the presence of economies of scope, giving incentives for farm diversification (Chavas and Aliber, 1993; Chavas and Di Falco, 2012; Kim et al., 2012; Paul and Nehring, 2005). In addition, diversification in agriculture can provide additional benefits from ecological services provided by agroecosystems (De Groot et al., 2002; Foster et al., 2011; Klasen et al., 2016; Priess et al., 2007).

Previous research has examined the technological and economic factors that influence farm diversification decisions (Bezabih and Sarr, 2012; Kurosaki, 2003; Meert et al., 2005; Mishra et al., 2004; Pfeifer et al., 2009; Smale et al., 2003). The literature has studied how such decisions have affected the relative gains of diversification (or specialization) in agriculture (Chavas and Di Falco, 2012; Di Falco and Chavas, 2006; Katchova, 2005; Kim et al., 2012; Rahman, 2009). A key argument involves distinguishing between productivity effects and risk effects of farm diversification.

Economies of scope imply cost reduction and productivity gains that provide incentives to diversify (Baumol et al., 1988; Coelli and Fleming, 2004; Kim et al., 2012). An example is the case of crop rotation that can contribute to enhancing soil fertility, interruption of disease cycle, increasing farm yields and improving agricultural productivity (Karlen et al., 2006; Krupinsky et al., 2002; Zentner et al., 2002). Alternatively, economies of scale and diseconomies of scope would generate productivity gains from specialization. Another contribution of diversified systems is their role in reducing exposure to risk. This seems particularly important in agriculture that typically faces extensive price risk as well as production risk. In the presence of weather shocks, insects and pest infestation and high price volatility, output specialization (e.g., monoculture) can be very risky (Ito and Kurosaki, 2009). And the overall risk exposure facing farmers may have increased with recent policy reforms that have reduced government policy interventions in EU agriculture (e.g., decoupling of farm support programs (Brady et al., 2009)). This raises many questions. What is the role of farm diversification in farmers' welfare? And what is the relative importance of risk versus productivity in farm diversification decisions? Answering these questions is important to understand the motivations toward output specialization (diversification) in agriculture. For example, some policy makers have expressed concerns that the rise of large and more specialized farms may not be desirable (European Commission, 2013). This stresses the need to understand better the economics of farm diversification, and its implications for both farm management and agricultural policy. While some progress has been made addressing this issue (Chavas and Di Falco, 2012), the exact nature of the economic relationship between risk and productivity in farm diversification strategies remains poorly understood. This provides the main motivation for this paper.

This paper presents an economic evaluation of farm diversification strategies, with an application to farm panel data from Germany. The analysis examines the relative role of risk management and productivity. The empirical investigation relies on an econometric estimation of production, productivity and risk. The analysis shows that farm diversification generates both productivity gains and reductions in the cost of risk. It also documents how the productivity gains and risk mitigation effects vary depending on the diversification scheme.

## II. Methodology

In this paper, we investigate the economic value of diversification. For this purpose, we follow the conceptual model introduced and employed in previous farm diversification literature (Chavas and Di Falco, 2012; Chavas and Kim, 2007; Kim et al., 2012).

The starting point is a welfare measure that can be used to support the analysis of both productivity and risk. Let $\pi$ denote the stochastic payoff with a given distribution function. Our analysis relies on the expected utility model where the farmer is assumed to maximize expected utility $EU(\pi)$, where $E$ is the expectation operator and $U(\pi)$ is a strictly increasing function representing the farmer's risk preferences. Our welfare measure is the certainty equivalent ($CE$), defined as the sure payoff satisfying $EU(\pi) = U(CE)$. Denote the expected payoff by $E(\pi)$. Under decisions $z$, the certainty equivalent can be written as (Pratt, 1964)

$$CE(z) = E(\pi(z)) - R(z) \tag{1}$$

where $R(z)$ is the risk premium.

For a given $z$, the risk premium $R(z)$ is the sure amount of money that a farmer is willing to give up to eliminate risk exposure (Arrow, 1965; Pratt, 1964). In general, the risk premium $R(z)$ depend on the farmer's risk preferences, with $R(z) > 0$ when the farmer is risk averse and exhibits a concave utility function $U(\pi)$. In this context, equation (1) shows that $R(z)$ measures the implicit cost of risk bearing. The cost of risk typically varies with the farm management decisions $z$ (as decisions $z$ affect the probability distribution of payoff $\pi$). Of special interest here is the role of farm diversification strategies as means of reducing risk exposure.

Consider a farm producing multiple outputs $y = (y_1, y_2, \dots, y_m)$ using multiple inputs $x = (x_1, x_2, \dots, x_n)$. Using the netput notation, netputs can be represented as $z \equiv (y, -x)$ where inputs are negative and outputs are positive. Under stochastic shocks $e$ (e.g., weather shocks), production feasibility is given by the set $F(e)$, where $z \in F(e)$ means that z can be feasibly produced under the random shocks $e$. In this context, the stochastic multi-output production function is

$$f(y_2, \dots, y_m, x, e) = Max_{y_1}\{y_1: (y_1, y_2, \dots, y_m, -x) \in Z(e)\} \tag{2}$$

In equation (2), $f(y_2, \dots, y_m, x, e)$ is the largest feasible output of $y_1$ can be obtained conditional on the other outputs $(y_2, \dots, y_m)$, on inputs $x$, and on the stochastic shocks $e$. Assume that production risk associated with the stochastic shocks $e$ is represented by a given probability distribution. In general, the production function in equation (2) can be written as follows.

$$y_1 = f_1(y_2, \dots, y_m, x, \beta_1) + u \tag{3a}$$

where $f_1(y_2, \dots, y_m, x, \beta_1) = E[f(y_2, \dots, y_m, x, e)]$, $E$ is the expectation operator based on the probability distribution of the shocks $e$, $\beta_1$ are parameters and $u$ is an error term with mean zero. Equation (2) captures the expected input and output relationships in the presence of production risk. As far as mean effects are concerned, it provides a first piece of information to evaluate the economics of farm diversification. But to the extent that risk matters, the analysis needs to go beyond just mean effects. For this, we rely on the moment-based approach to evaluate the role of risk in diversification decisions (Antle, 1983, 1987). From equation 3, the distribution of the error term $u = y_1 - f_1(y_2, \dots, y_m, x, \beta_1)$ reflects production risk. In general, the distribution of $u$ can also depend on the management decisions $z$. Let the second moment (the variance) of $u$ be

$$E(u)^2 = Var(\pi) = h_2(y_2, \dots, y_m, x, \beta_2) \tag{3b}$$

and the third moment (the skewness) of $u$ be

$$E(u)^3 = Skew(\pi) = h_3(y_2, \dots, y_m, x, \beta_3). \tag{3c}$$

Equations (3a), (3b) and (3c) will be used below in the empirical assessment for productivity and risk exposure.

In general, the stochastic payoff $\pi$ depends on the decisions $z$: $\pi(z)$. And the risk premium $R(z)$ can be written as a function of the moments of the payoff distribution. As showed in Chavas and Di Falco (2012), under the utlity fucntion $U(\pi)$, the risk premium can be expressed as:

$$R(z) = -\left(\frac{1}{2}\right)\frac{\left(\partial^2 U/_{\partial\pi^2}\right)}{\left(\partial U/_{\partial\pi}\right)}Var(\pi) - \left(\frac{1}{6}\right)\frac{\left(\partial^3 U/_{\partial\pi^3}\right)}{\left(\partial U/_{\partial\pi}\right)}Skew(\pi) \tag{4}$$

where $\frac{\left(\partial^2 U/_{\partial\pi^2}\right)}{\left(\partial U/_{\partial\pi}\right)}$ and $\frac{\left(\partial^3 U/_{\partial\pi^3}\right)}{\left(\partial U/_{\partial\pi}\right)}$ represent the degree of risk aversion for the decision maker. Under Constant Relative Risk Aversion (CRRA), the utility function $\mathrm{U}(\pi)$ takes the form $\mathrm{U}(\pi) = \pi^{1-\alpha}/(1-\alpha)$ for $\pi > 0$. Here, $\alpha$ represents the Arrow-Pratt relative risk aversion coefficient (Pratt, 1964). Following Chavas and Di Falco (2012), under CRRA, the risk premium in (4) can be written as :

$$R(z) = \frac{\alpha}{2}\,\frac{Var(\pi)}{E(\pi)} - \frac{\alpha(\alpha+1)}{6}\frac{Skew(\pi)}{[E(\pi)]^2} \tag{5}$$

From equation (5), the risk premium $R(z)$ can be decomposed into two parts

$$R(z) = R_{var} + R_{Skew} \tag{6}$$

where $R_{var} = \frac{\alpha}{2}\,\frac{Var(\pi)}{E(\pi)}$ is the variance component and $R_{Skew} = -\frac{\alpha(\alpha+1)}{6}\frac{Skew(\pi)}{[E(\pi)]^2}$ is the skewness component of risk premium. Under risk aversion, we have $\alpha > 0$, and equations (5) and (6) imply that $\frac{\alpha}{2} > 0$ and an increase in the variance increases the risk premium of the farm. In addition, $\alpha > 0$ implies downside risk aversion as $-\frac{\alpha(\alpha+1)}{6} < 0$ and an increase in skewness (reflecting a decline in exposure to downside risk) reduces the risk premium of the farm.

While the risk aversion coefficient can vary across individuals, most decision makers tend to be risk averse (with $\alpha > 0$). Empirical evidence indicates that the value of the relative risk aversion coefficient $\alpha$ varies typically from 1 (mild risk aversion) to 4 (a more extreme degree of risk aversion) (Gollier, 2001). Below, we will use equations (5) and (6) to evaluate the cost of risk. Of special interest will be to assess how the risk premium $R(z)$, the expected payoff $E(\pi(z))$ and the certainty equivalent $CE(z)$ vary across diversification strategies (as captured by the management decisions $z$).

The evaluation of economics of farm diversification relies on the following approach. Consider an integrated farm that can be split into $k$ specialized farms with $z_k, k = 1, 2, \dots, K$, and $2 \leq K \leq m$. In our empirical investigation, we want to compare the economic value of the original integrated farm and the $K$ "more specialized" farms. Our analysis is based on the comparison of the contribution of each system to farm productivity and risk management capacity.

The economic incentive to diversify (or disincentive to specialize) can be measured by the difference between the certainty equivalent of an integrated farm ($CE(z)$) and the summation of the certainty equivalent of each specialized farm ($\sum_{k=1}^{K} CE(z^k)$), holding aggregate resources constant. Thus, subject to the resource constraint $z = \sum_{k=1}^{K}(z^k)$, the economies of diversification can be defined as:

$$D(z, z^1, \dots, z^K) \equiv CE(z) - \sum_{k=1}^{K} CE(z^k) \qquad (7)$$

It follows from (7) that economies (diseconomies) of diversification exist if $D > (<)\ 0$. The restriction $z = \sum_{k=1}^{K}(z^k)$ is imposed to maintain the assumption that, at the aggregate, the same amounts of inputs are used to produce the same level of outputs. Economies of diversification $(D > 0)$ exist if the certainty equivalent $(CE)$ of producing outputs in an integrated manner is higher than the sum of the $CE$ of producing them in a more specialized system. This gain in certainty equivalent can arise from synergies in productivity of outputs and/or their role in mitigating risk in agriculture. Alternatively, diseconomies of diversification $(D < 0)$ exist when the sum of the certainty equivalent of the specialized productions is higher than the certainty equivalent obtained from an integrated farm.

To gain additional insights into the economics of diversification, we can further decompose the gain in CE (equation 3) in to different components (Chavas and Di Falco, 2012; Chavas and Kim, 2007; Coelli and Fleming, 2004; Kim et al., 2012). Following Chavas and Di Falco (2012, p. 37), the economies of specialization $D$ can be decompsed in three components

$$D = D_C + D_S + D_V \qquad (8)$$

where $D_C$, $D_S$ and $D_V$ are complementarity component, scale component, and concavity component, respectively. The decomposition in (8) provides useful insights in the sources of benefit from specialization schemes.

$D_C > 0$ indicates the presence of complementarity between outputs. Applied to the certainty equivalent $CE$ given in (1), complementarity benefits can come from the mean payoff $E(\pi)$ (when positive synergy among outputs means that the production of one output has a positive effect on the marginal expected product of the other outputs) as well as the risk premium $R$ given in (5)-(6) (in which case complementarity between outputs contributes to the reduction in the cost of risk). In either case, complementarity between outputs can motivate farm diversification.

Similarly, the scale component $D_S$ in (8) indicates that scale affects diversification incentives. Again, from (1), the certainty equivalent $CE$ in (7) includes both mean payoff $E(\pi)$ as well the cost of risk $R$ in (5)-(6). In the context of mean effects, Chavas and Di Falco (2012, p. 34) showed that $D_S \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} 0$ under $\begin{Bmatrix} \text{increasing} \\ \text{constant} \\ \text{decreasing} \end{Bmatrix}$ returns to scale $\begin{Bmatrix} \text{IRTS} \\ \text{CRTS} \\ \text{DRST} \end{Bmatrix}$, implying that the scale component $D_S$ contributes to economies (diseconomies) of diversification under IRTS (DRTS). Thus, a technology exhibiting IRTS provides extra incentives to diversify while DRTS provides incentives to specialize. This motivates analyses of any departure from constant returns to scale (CRTS) in productivity analysis (Chavas and Di Falco, 2012; Chavas and Kim, 2007; Coelli and Fleming, 2004; Paul and Nehring, 2005). Similar arguments apply to the cost of risk where scale can affect the risk premium $R$. For example, scale would provide extra incentives to diversify when the average risk premium declines with an increase in the scale of operation.

Finally, the concavity component $D_V$ in (8) reflects the concavity of the certainty equivalent $CE(z)$. Chavas and Di Falco (2012, p. 34-36) showed that $D_V \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} 0$ corresponds to the function $CE(z)$ being $\begin{Bmatrix} \text{concave} \\ \text{linear} \\ \text{convex} \end{Bmatrix}$. Applied to mean effects, it follows that a concave production function (exhibiting diminishing marginal productivity) contributes to economies of diversification. Alternatively, a convex production function would provide a disincentive for diversification. The concavity component $D_V$ also includes effects on the risk premium $R$: from (5), diversification can affect variance and skewness which in turn can affect $D_V$. The exact nature and magnitude of such effects are an empirical issue which we evaluate below.

## III. Econometric Approach

Our empirical analysis of exposure to production risk will rely on the specification and estimation of equations (3a), (3b) and (3c) applied to farm-level panel data. There are a number of econometric challenges that arise with the estimation of these equations. First, the specification of the multi-output system should be flexible enough to evaluate the role of diversification for productivity and risk mitigation of farms. For this, we include 7 outputs (wheat, barley, sugar beet, rapeseed, rye, potato and dry pulses) in a quadratic specification.

Second, there could be issues of unobserved heterogeneity (for instance difference in the managerial abilities, variability in agro-climatic conditions, etc.) across farms. One has to control for this unobserved heterogeneity as this might bias the estimation results. Panel data provides some options. If the unobserved heterogeneity is unique to each farm and is constant over time (e.g., time invariant characteristics of each farm), controlling for it can be done using fixed effects model (Wooldridge, 2010). Estimating a fixed effect model then produces consistent parameter estimates. However, the fixed effect model can involve loss in statistical efficiency. Alternatively, one can estimate the parameters using Hausman-Taylor approach (Hausman and Taylor, 1981) to obtain more efficient parameter estimates. The Hausman-Taylor approach is an instrumental variable regression method to control for the correlation between the time invariant characteristics of the farm and other explanatory variables. This approach makes use of the mean of endogenous variables and other time invariant characteristics as instruments.

Finally, the unobserved heterogeneity between farms could be time variant. Such unobserved characteristics to the econometrician could lead to coefficient bias. In this case, an Instrumental Variable (IV) estimation is suggested to control for endogeneity problem (Wooldridge, 2010). Accordingly, we employ instrumental variable technique with first year lag of inputs and outputs as instruments. With the presence of adjustment costs and dynamics in the farm, lagged values are usually considered as relevant instruments (Arellano and Bond, 1991; Blundell and Bond, 1998; Roodman, 2009). As we recover the error term $u$ from equation (3a), the issue of unobserved heterogeneity might also prevail in the second and third moment specifications (3b) and (3c). To control such a bias, we again employ a similar IV estimation method.

## IV. Data

This paper investigates the economic value of farm diversification in arable farms in Germany using an unbalanced panel of Farm Accountancy Data Network (FADN) from 1989 to 2009.

For this empirical analysis, we use a total of 30503 farm observations. There is a general increase in the average farm size of the sample through time (from around 50 hectares in 1989 to around 200 hectares in 2009). The income of the sample farms ranges from a large negative value (loss) to a large positive value (gain), with a mean of about 113756 euros.

In the production function estimation, we include the major outputs produced on farms in Germany. The major agricultural outputs produced in the region include wheat (grown by 89% of the sample), barley (grown by 82% of the sample), sugar beet (grown by 57% of the sample), rapeseed (grown by 56% of the sample), rye (grown by 37.8% of the sample), potato (grown by 25% of the sample) and dry pulses (raised by about 16% of the sample). We employ this seven outputs (wheat, barley, sugar beet, rapeseed, rye, potato and dry pulse) as a large proportion of the sample is engaged in arable crop activities. The average arable crops produced by farms in the sample is about 4.8 crops per farm. It is worthwhile to note that the sample does not show notable trends in farm diversification over the years 1989 to 2009.

Table 1: Descriptive statistics

| Variables | % of zero values (x=0) | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|
| Land in hectares | | 197.74 | 427.23 | .43 | 6263 |
| Seed in euros | .01 | 10384.98 | 24344.89 | 0 | 690988.3 |
| Labor in hours | | 7441.69 | 17150.04 | 71 | 450840 |
| Fertilizer in euros | .02 | 16014.11 | 34495.68 | 0 | 780489.4 |
| pesticides in euros | .03 | 15196.12 | 31548.42 | 0 | 526870.3 |
| Energy in euros | .001 | 15415.72 | 37263.88 | 0 | 848903.3 |
| Wheat in quintals | 11.18 | 386.42 | 942.31 | 0 | 28762.3 |
| Barley in quintals | 18.03 | 179.26 | 426.48 | 0 | 8447.8 |
| Sugar beet in tones | 42.90 | 513.64 | 1057.72 | 0 | 30607.7 |
| Rapeseed in quintals | 43.82 | 83.09 | 231.96 | 0 | 4867.3 |
| Rye in quintals | 62.20 | 61.31 | 253.62 | 0 | 8983.7 |
| Potato in quintals | 74.78 | 131.29 | 583.88 | 0 | 21067.2 |
| Dry pulses in quintals | 84.06 | 13.38 | 62.88 | 0 | 1782.8 |
| Age of the manager | | 52.00 | 10.84 | 18 | 99 |
| Gross margin (Euros) | | 113756.6 | 252652.1 | -682531 | 5417332 |

In the multi-output specification, we include inputs used for the crop production activities. Land is measured in hectares and labor in hours. For other inputs (fertilizer, pesticides and energy), we obtain quantity indexes by dividing the value of each input by the corresponding national input price index (Eurostat, 2016). We further include dummies of fertilizer and pesticide, age of the manager, dummy of less favored area[28], year and regional dummies in the estimation.

**V. Econometric estimation**

Table 2 presents the production function estimation of equation (3a) using alternative approaches. We do the estimation with the random effects[29], fixed effects, Hausman-Taylor and instrumental variable approaches. This panel data consists of 30503 observations for the years from 1989 to 2009. Wheat is a major crop in Germany and 89% of the farms do produce the crop. Hence, we consider wheat production in tons as the dependent variable in the multi-output specification.

We get similar parameter estimates in the fixed effect and Hausman-Taylor approach. But we find considerable differences in the parameter estimates between the random effect and fixed effect methods. The Hausman test (with the Chi-square = 4459.5 and a p-value = 0.001) rejects the null hypothesis of no=difference between the Random effect and fixed effect estimation results. This reveals the presence of endogeneity due to the unobservable individual effects when fixed effects are ignored in the estimation. We employ regional dummies and the lagged values of input and output measures as instruments in the Hausman-Taylor approach. The Hausman test between the fixed effects estimation and the Hausman-Taylor approach confirms (with a Chi-square of 15.6 and p-value of 0.9) that there is no significant difference between the two.

Next, we consider the IV estimation method. We employ the first year lag of the input and output measures as instruments in the IV regression, allowing the IV approach to control for the endogeneity in inputs and outputs. The test statistic (Anderson canonical correlation LM statistic = 1995.95 and p-value = 0.000, Cragg-Donald Wald F statistic = 182.85) indicates that, in the IV estimation, the parameters are identified and we have strong instruments. We compared the estimates from the fixed effect and Hausman-Taylor approach with the estimates of the IV regression technique. Using a Hausman test, we find strong statistical evidence of

[28] Less-favored area (LFA) represents an area with natural handicaps (lack of water, climate, short crop season and tendencies of depopulation) or located in mountainous or hilly region ((OECD, 2001))

[29] The random effect estimates are not presented here. They are available from the authors upon request.

differences between the IV estimates and the estimates from the other approaches. We interpret this result as evidence of endogeneity of inputs and outputs (these variables being correlated with the error terms). On that basis, all the results and discussions presented below rely on IV estimates. The productivity of the farm improves with the age of the farm manager. In the same way, farms in less favorable areas produce less compared with farms in more favorable areas.

Table 2: Production function estimation

| Model | Fixed effects (N=30503) | Hausman Taylor (N=30503) | IV reg (N=21391) |
|---|---|---|---|
| Barley | -.021*** (.007) | -.021*** (.007) | -.252*** (.016) |
| Sugar beet | .062*** (.006) | .069*** (.006) | .184*** (.006) |
| Rapeseed | .064*** (.006) | .064*** (.005) | .233*** (.021) |
| rye | -.054*** (.005) | -.055*** (.004) | -.330*** (.009) |
| Potato | -.011* (.006) | -.009* (.005) | -.093*** (.005) |
| Dry pulse | -.029*** (.004) | -.029*** (.004) | .053*** (.009) |
| Barley^2 | -.008*** (.001) | -.008*** (.001) | .017*** (.002) |
| Sugar beet^2 | -.011*** (.001) | -.011*** (5.9e-04) | -.011*** (.001) |
| Rapeseed^2 | .008*** (7.5e-04) | .008*** (.001) | -.011*** (.002) |
| Rye^2 | -4.2e-04* (2.4e-04) | -4.0e-04* (2.2e-04) | .006*** (4.1e-04) |
| Potato^2 | -1.2e-04 (3.3e-04) | -1.6e-04 (3.1e-04) | .001*** (3.2e-04) |
| Dry pulse^2 | .003*** (4.2e-04) | .003*** (3.9e-04) | -.005*** (.001) |
| Barley* Sugar beet | .024*** (.001) | .024*** (.001) | .007*** (.002) |
| Barley* Rapeseed | .003* (1.4e-04) | .003** (1.3e-03)) | -.006** (.003) |
| Barley*rye | .012*** (.001) | .011*** (.001) | .004** (.002) |
| Barley*Potato | .005*** (.002) | .005*** (.003) | .016*** (.002) |
| Barley*dry pulse | -.001 (.001) | -8.3e-04 (8.8e-04) | -.001 (.001) |
| Sugar beet*Rapeseed | -.003** (.001) | -.003*** (.001) | .014*** (.002) |
| Sugar beet*rye | -.008*** (.001) | -.008*** (.001) | 3.6e-04 (.001) |
| Sugar beet*Potato | 3.3e-04 (.001) | 2.2e-04 (.001) | -.012*** (.001) |
| Sugar beet*dry pulse | .007*** (.001) | .007*** (.001) | .013*** (.001) |
| Rapeseed*rye | .002** (.001) | .002** (.001) | -2.2e-04 (.001) |
| Rapeseed*Potato | -.009*** (.001) | -.009*** (.001) | -.006*** (.002) |
| Rapeseed*dry pulse | .002* (.001) | .002** (.001) | .010*** (.001) |

| | | | |
|---|---|---|---|
| Rye*potato | -.004***(4.4e-04) | -.004***(4.1e-04) | -.008***(.001) |
| Rye*dry pulse | 4.4e-04 (6.9e-04) | 4.3e-04 (6.5e-04) | -3.2e-04 (.001) |
| Potato*dry pulse | .007***(.001) | .007*** (.001) | .003 (.002) |
| Land | .345***(.014) | .341***(.013) | .178***(.021) |
| Seed | -.020***(.003) | -.019***(.003) | -.085*** (.008) |
| Labor | -.055***(.008) | -.055***(.007) | -.042***(.009) |
| Fertilizer dummy | -.003 (.011) | -.001 (.010) | -.043**(.018) |
| Fertilizer | .078***(.004) | .078***(.004) | .243***(.020) |
| Crop protection dummy | .015 (.013) | .017 (.012) | -103***(.016) |
| Crop protection | .135***(.007) | .138***(.007) | .580***(.016) |
| Energy | .067***(.008) | .067***(.007) | -.031***(.011) |
| Age of the manager | 4.7e-04**(2.3e-04) | 4.4e-04**(2.1e-04) | 1.8e-04 (2.4e-04) |
| Less favorable area | .009 (.007) | -.013** (.006) | -.038***(.006) |

Note: *, ** and ***indicate significance levels at 10%, 5% and 1% probabilities. Standard errors are presented in parenthesis. The coefficients of regional and year dummies are not reported here to save space.

Most of the output and input parameters are statistically significant. This result is found to hold across estimation methods. The signs and magnitudes of the output coefficients are crucial in the evaluation of the benefit of diversification (as further investigated below). From Table 2, the signs of the coefficients of the cross outputs are positive for some outputs and negative for others. Positive cross coefficients correspond to situations of complementarity where one output has a positive effect on the expected marginal product of another output. Alternatively, negative coefficients of the cross terms indicate the presence of competition between different arable crop activities. There are also positive and negative coefficients of the square terms of outputs. These results indicate that the productivity gain from farm specialization (diversification) can vary with the choice of outputs. Some crops could perform better in an integrated farm when the scope economies between outputs outweigh the possible competition for resources. Conversely, some forms of diversification (for instance cultivating crops with less or no synergies in an integrated farm) can be worse off in terms of productivity compared with the specialized production system. Previous empirical works in both developed and developing countries present mixed results in this regard (Havlík et al., 2005; Rahman, 2009; Zhu and Lansink, 2010). Zhu and Lansink (2010) for instance present negative production elasticities between root crops and cereals, and other products and cereals, while positive production elasticities between other crops and cereals in Germany. Similarly, Havlík et al. (2005) show both competition and complementarity of production between beef and biodiversity with output price uncertainty in a case study in France. Rahman (2009) also document the presence of diversification economies through some integrated production patterns in Bangladesh. According to Rahman (2009), the difference in the seasonality and intensity of labor demand between modern and traditional rice varieties majorly explain the existing complementarities in production. Kim et al. (2012), in their empirical analysis from a sample of Korean farms, show the presence of a mix of concave and convex production technology. We will further explore and discuss the benefit of different forms of diversification in arable farms in the next section.

In Table 3, we present the estimation results of the variance equation (3b) (second moment) and skewness equation (3c) (third moment) using an instrumental variable approach. Most of the production inputs, outputs, cross and square terms of the outputs are statistically significant in the variance and skewness equations.

Table 3: Variance and skewness functions (Instrumental variable Approach)

| Model | Variance | skewness |
|---|---|---|
| Barley | -.114$^{***}$ (.016) | .055 (.069) |
| Sugar beet | -.002 (.006) | 8.5e-04$^{***}$(.029) |
| Rapeseed | -.101$^{***}$(.021) | -841$^{***}$(.091) |
| rye | -.066$^{***}$(.010) | -.149$^{***}$(.043) |
| Potato | -.023$^{***}$(.005) | -.069$^{***}$(.022) |
| Dry pulse | .069$^{***}$(.010) | .157$^{***}$(.043) |
| Barley^2 | .019$^{***}$ (.002) | .026$^{***}$(.008) |
| Sugar beet^2 | -.004$^{***}$(.001) | -.003 (.004) |
| Rapeseed^2 | .047$^{***}$(.002) | .246$^{***}$(.007) |
| Rye^2 | -.006$^{***}$(4.2e-04) | -.014$^{***}$(.002) |
| Potato^2 | .003$^{***}$(3.3e-04) | .017$^{***}$(.001) |
| Dry pulse^2 | -.006$^{***}$(9.6e-04) | -.004 (.004) |
| Barley* Sugar beet | .014$^{***}$(.002) | .047$^{***}$(.009) |
| Barley* Rapeseed | -.054$^{***}$(.003)) | -.178$^{***}$(.012) |
| Barley*rye | .039$^{***}$(.002) | .076$^{***}$(.009) |
| Barley*Potato | -.001 (.003) | .045$^{***}$(.011) |

| | | |
|---|---|---|
| Barley*dry pulse | .009$^{***}$(.002) | .026$^{***}$(.007) |
| Sugar beet*Rapeseed | -.009$^{***}$ (.002) | -.051$^{***}$(.007) |
| Sugar beet*rye | -.016$^{***}$ (.002) | -.059$^{***}$(.006) |
| Sugar beet*Potato | -2.2e-04 (.001) | .009 (.006) |
| Sugar beet*dry pulse | 2.2e-05 (9.9e-04) | .001 (.004) |
| Rapeseed*rye | .003$^{*}$ (1.5e-04) | .069$^{***}$(.006) |
| Rapeseed*Potato | -.017$^{***}$(.002) | -.115$^{***}$(.007) |
| Rapeseed*dry pulse | -.018$^{***}$(.001) | -.097$^{***}$(.005) |
| Rye*potato | -2.2e-04 (.001) | -.010$^{*}$ (.005) |
| Rye*dry pulse | .009$^{***}$(.002) | .013$^{**}$ (.006) |
| Potato*dry pulse | -.002 (.002) | .011 (.008) |
| Land | .096$^{***}$(.013) | .047 (.057) |
| Seed | .039$^{***}$(.008) | -.023 (.033) |
| Labor | -.058$^{***}$(.009) | .257$^{***}$(.041) |
| Fertilizer dummy | 9.0e-05 (.019) | .061 (.082) |
| Fertilizer | .092$^{***}$(.021) | -.056 (.091) |
| Crop protection dummy | .029$^{*}$ (.017) | .093 (.072) |
| Crop protection | .086$^{***}$(.016) | .408$^{***}$(.071) |
| Energy | .067$^{***}$(.007) | -.428$^{***}$(.049) |
| Age of the manager | -8.7e-05 (2.4e-04) | 6.4e-04 (.001) |
| Less favorable area | .010 (.007) | .063$^{***}$(.027) |

Note: *, ** and ***indicate significance levels at 10%, 5% and 1% probabilities. Standard errors are presented in parenthesis. The coefficients of regional and year dummies are not reported here to save space.

For both variance and skewness, some coefficients of the output interaction terms are positive, while others are negative. Some outputs are complementary as they reduce the variance of production (see for example the effect of barley with rapeseed, sugar beet with rapeseed and rye etc.). Conversely, there are output interactions that are variance increasing (barley with sugar beet, rye and dry pulse, rye with rapeseed and dry pulse etc.). The signs of coefficients for squared output terms are mixed. These results indicate that the benefit of diversification (from risk reduction) depends on the cropping choice. With diversification, it is possible to reduce the variability in production (from environmental stress or pest damage) through the inclusion of crops that are resilient to these stresses. Then, farms relying on multiple production activities can benefit from a reduced variance in production. This can happen when a specific production condition favors some crop types while has a detrimental effect on others. On the other hand, there may not be any benefit from diversification through enterprise mix when a certain shock (e.g. climate variability or pest damage) has similar effect on all activities.

Table 3 also reports the output interaction terms in the skewness function. Again, some terms are positive while other are negative. The output interaction effects on skewness are positive between barley and sugar beet, rye, potato and dry pulse, between rapeseed and rye, and between rye and dry pulse. These positive output interactions contribute to reducing exposure to downside risk. But some output interaction effects are negative in the skewness equation. This includes interactions between barley and rapeseed, and between sugar beet and rapeseed and rye. The negative output interactions in the skewness equation increase downside risk. Again, this indicates that diversification effects on the downside risk vary with the production scheme. This also confirms differences in risk management potential of different crop mixes in response to shocks (e.g. climate change, or pest damage). While these results document that farm diversification can affect risk exposure (through variance and skewness), this raises two questions. How does it impact farmer welfare? And how do such effects vary across diversification strategies? These issues are addressed in the following section.

**VI. Economic value of farm diversification**

In the previous section, we documented the presence of heterogeneity in the effects of different outputs on the mean, variance and skewness functions in a multi-output production setting. The results indicate that the gain from farm diversification is likely to depend on the mix of commodities that the farm grows. In this section, we discuss the implications of diversification for farmer's welfare, as measured by $D$ in equation (7). Using equation (7), the analysis relies on comparing the certainty equivalent (CE) of an average diversified farm (including both expected income and risk premium; see equation 1) with the sum of CE across specialized farms, holding total resource constant. As presented on (6), the overall effect of diversification on the cost of risk is the sum of its contribution to the risk premium from the variance component and the skewness component ($R = R_{Var} + R_{skew}$). For a risk averse farmer, welfare gains from farm diversification can come from a decrease in the risk premium due to a decrease in variance and/or an increase in skewness (i.e. a decrease in downside risk). The evaluation of risk requires information about the risk preferences of the decision makers (equation 5). Assuming constant relative risk aversion (CRRA), the relative risk aversion coefficient $\alpha$ summarizes the degree of risk aversion of the farmer. As noted above, empirical findings have shown that the relative risk aversion coefficient $\alpha$ varies between 1 (mild risk aversion) to 4 (a more extreme level of risk aversion) (Gollier, 2001) Our evaluation of risk premium is based on a risk aversion coefficient of $\alpha = 1$.[30] In this context, the variance and skewness components of risk premium is given in (5)-(6), with $R_{var} = \frac{1}{2}\frac{Var(\pi)}{E(\pi)}$ and $R_{Skew} = -\frac{1}{3}\frac{Skew(\pi)}{[E(\pi)]^2}$. In our evaluation, we do not consider price uncertainty.[31] Accordingly, we use an average price of 112 euros for a quintal (100kg) of wheat. Using equation (7), we then evaluate the welfare gain (loss) of farm diversification under selected diversification scenarios. The analysis uses the estimation results reported in the previous section. We use equation (1) to separate the mean effects from the risk effects, where the risk effects involve mean and variance effects as given in equations (5) and (6). Finally, we use equation (8) to decompose the welfare effects into complementarity, scale and concavity components.

We start with an average integrated farm (200 ha) growing different combination of crop outputs, and evaluate the welfare of this integrated farm. Afterwards, we examine the welfare of partially specialized farms, each one partially specializing in one output. As our sample doesn't have a farm with complete specialization, we consider scenarios of partial specialization, where the original farm is split into more specialized farms. We use a degree of specialization coefficient θ=0.8, where a farm produces one crop in 80% of the land and the remaining 20% land being equally divided among the remaining outputs. We then compare the productivity, risk premium and the certainty equivalent of the integrated farm and the "more specialized" farms using (7).

We consider four different scenarios (S1, S2, S3 and S4) that approximate farm situations observed in the sample. These scenarios vary with the type and number of crop production activities. Under scenario S1, we examine the welfare of an integrated farm equally distributing its land among 4 crops: wheat, barley, rye and rapeseed production. And, we compare the welfare of this integrated farm with the welfare of four farm types, each one partially specialized in producing similar outputs. Under scenario S2, we evaluate the welfare of an integrated farm

[30] We conducted a sensitivity analysis on the parameter $\alpha$. As expected, we found that increasing $\alpha$ increases the risk premium $R$ and its components given in (6). But besides this result, we found that other findings reported below remained qualitatively similar.

[31] This implies that the analysis considers production risk as the most important source of risk in the EU. As previous empirical works (e.g. Koundouri et. al., 2009) suggest, production risks dominate market risks in the EU as price protection policies are in place for major crops in through the CAP.

producing 4 crops (wheat, rye, potato and rapeseed). Note that S1 and S2 both include 4 crops, but switching from S1 to S2 involves replacing barley by potato. Scenario S3 considers an integrated farm producing 5 outputs (wheat, barley, rye, rape seed and potato). Finally, under scenario S4, we consider an integrated farm producing 6 arable crops (wheat, barley, rye, rapeseed, sugar beet, pulse). Thus switching from S1 or S2 toward S3 or S4 involves increasing the number of crops from 4 to 5 under S3, and to 6 under S4. The estimates of diversification benefits are presented in Table 5 for each of the 4 scenarios.

Table 4: Economic value of diversification (θ=0.8)

| Scenarios | Diversification benefits (costs)[32] in Euros for | Overall effect, $D$ | Complementarity Effect, $D_C$ | Scale effect, $D_S$ | Concavity Effect, $D_C$ |
|---|---|---|---|---|---|
| S1 (wheat, barley, rye, rapeseed) N=5394 | Mean component, E | 7320.98***(1632.99) | 806.19 (1838.13) | 446.59*** (21.32) | 6068.19*** (598.72) |
| | Risk premium from variance, $R_V$ | -9189.54*** (854.47) | -4507.38*** (962.41) | -116.59*** (11.16) | -4565.57*** (313.48) |
| | Risk premium from skewness, $R_s$ | 14671.69***(2379.16) | 4780.93*(2679.68) | 187.12***(31.08) | 9703.65***(872.83) |
| | Risk premium ($R = R_V + R_s$) | 5482.15 | 273.55 | 70.53 | 5138.08 |
| | Certainty Equivalent, CE = E - R | 12803.13 | 1079.74 | 517.12 | 11206.27 |
| S2 (wheat, rye, potato, rapeseed) N=3102 | Mean component, E | -11410.1***(4876.79) | -27553.86***(4889.7) | 455.97*** (29.04) | 15687.78*** (2701.44) |
| | Variance component of risk, $R_V$ | 7553.62*** (2553.39) | 17206.73*** (2560.1) | -97.38*** (15.20) | -9555.73*** (1414.42) |
| | Skewness component of risk, $R_s$ | -34141.64***(7109.54) | -77721.61***(7128.3) | 281.65***(42.33) | 43298.31 (3938.24) |
| | Risk premium ($R = R_V + R_s$) | -26588.02 | -60514.88 | 184.27 | 33742.58 |
| | Certainty Equivalent, CE = E - R | -37998.12 | -88068.74 | 640.24 | 49430.36 |
| S3 (wheat, rye, barley, rapeseed, potato) N=2894 | Mean component, E | 30656.67***(4852.82) | 17822.93*** 4556.48) | 228.63*** (10.38) | 12605.12*** (1713.75) |
| | Variance component of risk, $R_V$ | 6868.12*** (2540.84) | 14489.16***(2385.68) | -50.20*** (5.44) | -7570.84*** (897.29) |
| | Skewness component of risk, $R_s$ | 1922.76 (7074.59) | -25887.68*** 6642.57) | 87.25*** (15.14) | 27723.19*** (2498.36) |
| | Risk premium ($R = R_V + R_s$) | 8790.88 | -11398.52 | 37.05 | 20152.35 |
| | Certainty Equivalent, CE = E - R | 39447.55 | 6424.41 | 265.68 | 32757 |
| | Mean component, E | -44468.47***(6561.68) | 69025.95***(6201.16) | -22.88*** (.941) | -113471.5*** (9657.07) |

[32] Diversification benefit (cost) is measured in Euros.

| | | | | | |
|---|---|---|---|---|---|
| S4 (wheat, barley, rye, rapeseed, sugar beet, pulse) N=2447 | Variance component of risk, $R_V$ | 14020.97***(3435.56) | -1795.59 (3246.8) | -1.595*** (.493) | 15818.17*** (5056.24) |
| | Skewness component of risk, $R_s$ | -17627.55* (9565.81) | -13860.3 (9040.24) | 2.399* (1.372) | -3769.65 (14078) |
| | Risk premium ($R = R_V + R_s$) | -3606.58 | -15655.89 | 0.804 | 12048.52 |
| | Certainty Equivalent, CE = E - R | -48075.05 | 53370.06 | -22.076 | -101422.98 |

Notes: *, ** and ***indicate significance levels at 10%, 5% and 1% probabilities. The numbers in brackets indicate bootstrapped standard errors. The benefit of diversification on the certainty equivalent is the additive value of its effect on the mean and on the risk premium of farms (CE=mean-Risk premium)

Table 4 shows that different patterns of farm diversification produce different welfare results. This reflects that the gains from diversification vary with the mix of crops in each diversification scheme. These differences come from the mean, variance and skewness effects reported above (see Tables 2 and 3).

First, let's start by discussing the role of farm diversification on the productivity of the farm based under the first scenario. In the case of wheat, barley, rye and rapeseed combinations in the farm, we find that the productivity of diversified form of production of these crops is superior to specialized form of production. A diversified farm generates benefit of about 7320 euros compared to production of these crops in partially specialized farms. This value amounts to 6.43% of the gross margin of an average farm in the sample. This shows strong incentives for farm diversification. The decomposition of this gain to complementarity, scale and concavity components is also reported in the above table. The complementarity effect of outputs in scenario 1 is positive but not statistically significant. The scale component is positive and statistically significant ($D_S$ =446 euros). This implies that IRTS in this scenario contributes to the gain with diversification. In the same way, concavity component contributes to the gain from diversification ($D_v$=6068 euros). This gain is equivalent to 5.3% of the sample gross margin. The positive concavity component indicates that the underlying technology is concave with respect to the outputs and exhibit diminishing marginal productivity. In this diversification scenario, the concavity and scale components contribute to positive economic benefits from farm diversification.

Table 4 also reports the contribution of farm diversification for risk premium from the variance and skewness components under scenario S1. The output combinations in this integrated farm are variance increasing. A diversified farm has a significantly higher variance compared to the variance of partially specialized farms, and contribute to an increase in the risk premium ($R_{var}$=-9189 euros). This is equivalent to 8% of the average gross margin in the sample. On the other hand, an integrated farm of this type contributes to the reduction of the downside risk. This diversification pattern has significantly contributed towards positive skewness (decrease in the downside risk) of the income of arable farms. The gain on the reduction of risk premium from skewness component amounts to 12.9% of the average gross margin ($R_{skew}$=14671.69 euros). Under this scenario (S1), the skewness component dominates the variance component, and risk gives an incentive for farm diversification. This stresses the importance of going beyond a simple mean-variance approach in risk analysis. In terms of risk reduction, diversification contributes to a reduction in the cost of risk of 5482 euros. This is equivalent to 4.8% of the sample mean gross margin. Similar findings on the role of the skewness component in explaining the role of diversification for risk management were also reported by Chavas and Di Falco (2012) from their work in Ethiopia. They report that effects of diversification on the variance component are not significant. On the other hand, Kandulu et al. (2012) show an important role of the variance of the expected income in influencing the decision to diversify or specialize in Australia. These empirical evidences imply that the role of the skewness and variance component on the overall risk premium can be situation specific.

Under Scenario S1, the complementarity, scale and concavity effects are statistically significant and have got similar signs for the variance and skewness of income. This implies that while all the three components of the variance give an incentive for specialization, the gain from the skewness component favors diversification. This illustrates how the role of diversification for risk mitigation depends on the strength of these effects on the variance and skewness components.

Table 4 also reports the certainty equivalent gain $CE$ from diversification. Under scenario S1, diversified farms have a welfare gain of 12803 euros as compared with production of these outputs in more specialized farms. This value amounts to 11.25% of the gross margin of the average farm in the sample. As discussed, this welfare gain from diversification includes both a mean productivity effect and a risk reduction effect. This indicates that, an integrated farm of wheat, barley, rye and rapeseed does improve farm welfare (as measured with CE) compared with partially specialized farms of these crop activities. This result is in line with the findings of Chavas and Di Falco (2012) in Ethiopian farms that documents the presence of strong welfare incentives for farm diversification.

Table 4 shows gains from diversification across the scenarios S1-S4. The results show that such gain can vary across farming practices. The gain in productivity from farm diversification obtained under scenario S1 completely disappears when we replace barley with potato (under scenario S2). Farms engaged in wheat, rapeseed, rye and potato combination has lower productivity compared to those producing these activities in specialized manner. This indicates that the integration of potato with these cereal and oil crop production activities does not generate productivity benefit. Unlike scenario S1, the scale and concavity components are working against the complementarity effect under scenario S2. In this scenario, the complementarity effect (negative) dominates the scale and concavity effects of the outputs. Under scenario S2, the gain from diversification is negative

($D = -37998$) and there this is a strong incentive to specialize. In this case, introducing potato in the diversification scheme eliminates the welfare gains from farm diversification.

Under scenario S3, the productivity gain from diversification increases to about 30000 euros (26.4% of the mean gross margin). And economies of diversification are positive and large, with $D = 39447$. Compared to scenarios S1 or S2, scenario S3 indicates that increasing the number of crops from 4 to 5 can sharply increase the benefit of farm diversification. But such results are reversed under scenario S4. While S4 includes 6 crops, it shows that introducing pulse and sugar beet in the cropping scheme has negative effects on farm productivity and on the gain from diversification. Under scenario S4, the effect of diversification on mean productivity amounts to a loss of -44000. In this diversification pattern, the complementarity effect works against the scale and concavity components. The negative and statistically significant effect of the concavity component show that there is part of the production function which doesn't exhibit diminishing marginal productivity. And, the positive complementarity effect from these diversification pattern is offset with the negative concavity effect. This means that the introduction of sugar beet and pulse in this integrated farm is not beneficial, providing a disincentive for farm diversification.

Note that the scale component reported in Table 4 is small in magnitude in most scenarios. In other words, economies of scale do not seem to be an important motivation for farm diversification (or specialization). Overall, table 4 shows that the productivity gain from farm diversification can be large (e.g., under scenarios S1 and S3). But the magnitudes and sources of such gain can vary a lot across different combinations of crops. As these results indicate, some crop activities are likely to perform better (in terms of productivity) as a sole crop compared to when they are produced in an integrated pattern. Conversely, some agricultural activities can combine to improve farm productivity in an integrated pattern (scenario S1 and scenario 3). In line with our empirical finding, previous studies highlight the possible gains (losses) from diversification, and difference in the sources of these gains (losses) depending on the production technologies. Kim et al. (2012) for instance report differences in productivity gains depending on whether rice is part of the farming system. They show incentives of specialization and diversification depending on the production technology in the farm. For instance, they found out that specialization is beneficial when the (non)convexity effect dominates complementarity effect in rice dominated production system in Korea.

Table 4 also shows how the role of risk can vary across scenarios. A shift from scenario S1 to scenario S2 can enhance the gain of diversification from the reduction in the cost of risk from the variance component. Nonetheless, the shift also leads to a significant loss of the value of diversification from the skewness component. Under scenario S2, the scale and concavity components work against the gain from the complementarity component towards reducing risk. A shift to Scenario S3 (wheat, barley, rye, rape seed and potato combinations) lead to a welfare gain from diversification from the reduction of the cost of risk from the variance component. Despite the welfare gain from the variance component in Scenario 4, this kind of diversification leads to a welfare loss of about 3600 euros. From table 4, note that the skewness component (downside risk) often contributes to a large reduction in the cost of risk (with the exception of scenario S3). Again, this stresses the importance of going beyond a simple mean-variance analysis.

Similar to the case of the value of farm diversification on productivity and risk premium, the contribution of farm diversification to the certainty equivalent varies across different scenarios. The benefit of diversification $D$ goes from +12803 euros under scenario S1 to -38000 euros under scenario S2 (i.e., if we replace barley with potato). As discussed in the components of the certainty equivalent (productivity and risk premium), this variability is evident across different combinations of arable crop outputs. While all the complementarity, scale and concavity components work in the same direction in scenario S1 and S3, the latter two work against the complementarity component in scenario S2 and S4.

Overall, we find that farm diversification can significantly influence productivity and the cost of risk. Farm diversification pays off when the activities have positive synergies to improve productivity or reduce risk premium on the farm. But the contribution of diversification to farm productivity and risk reduction varies across farming systems. Our analysis shows that the welfare effects of diversification are positive under scenario S1 (wheat, barley, rye, rape seed) and scenario S3 (wheat, barley, rye, rape seed and potato). In such situations, there are strong incentives to farm diversification. But such incentives disappear under scenarios S2 and S4. Comparing S1 and S3 shows that introducing potato in the crop rotation is associated with incentives to specialize. Similarly, scenario S4 indicates that introducing sugar beet or pulse in the farming system generates specialization incentives. As can be seen from the results, it is difficult to simply associate a gain or loss with the inclusion of a single crop. The interactions among crop activities are the key to determine the welfare benefit of farm diversification. There is a mix of findings in previous literature in this regard. Chavas and Di Falco (2012) document the welfare gain from diversification in agriculture in Ethiopia. Kandulu et al. (2012) on the other hand argue that the gain diversified system is situation specific. According to their finding, on moderate to high rain fall areas of Australia, farms can benefit from integrated farm through the combination of risk reducing effects of sheep production activities and high returns from lupin production. Nonetheless, this effect is unlikely to exist in dryland areas (ibid). Our paper also presents that the sources of the welfare gain (loss) can be different for different combinations of crops in the integrated farm. The magnitude and direction of the complementarity, scale and concavity effects of diversification determines the overall gain. This implies that unique crop combination scenario determines the underlying property of the production technology, and this influences the benefits (loses) associated with farm diversification. Unlike some previous empirical studies, we show that not all forms of diversification payoff: the gains (losses) from diversification of arable farms vary with the choice of activities in the farm portfolio.

## VII. Summary and conclusions

This article analyzes the economic value of farm diversification using a panel data of arable farms from 1989 to 2009 from Germany. The empirical investigation is based on a multi-output production function specification to compare certainty equivalent from diversified and partially specialized farms. This approach enables us to compare productivity and the risk premium of diversified and partially specialized farms estimated from the first, second and third moments of the production function. We further decompose the productivity and risk premium effects in to complementarity, scale and concavity components to explore the sources of the gains (losses) of diversification. The empirical analysis shows that diversification can give significant welfare gain through increasing productivity and reducing the cost of risk. Depending on the type of crop activities in the integrated farm, the magnitude and direction of the complementarity, scale and concavity effects of diversification determines the overall gain. In some diversification pathways, the scope effect from complementarity, scale effect and the existence of diminishing marginal productivity between outputs work in the same direction. We show cases where these effects contribute towards improving productivity and reducing the cost of risk. Conversely, these components can also work against each other in some diversification pathways. In such cases, the welfare gain (loss) from a diversification path is determined by the direction of the effect and relative importance of these components. In this paper, we show that there exist significant variations in the magnitude of productivity gains across different farming systems. Similar findings are obtained about the benefit of farm diversification towards reducing risk. Such benefits also differ between variance effects and skewness effects (the latter reflecting downside risk). While the skewness effect dominates in some diversification paths, the variance effect constitutes most of the risk premium in others. In our empirical analysis, we show that the contribution of diversification to the overall welfare of the farm varies across different combinations of outputs. We also show that the benefit of diversification can erode in some combinations of outputs. The latter happens when some crop mixes compete and reduce farm productivity or raise the cost of risk. Then, specialized farms would be more efficient. For instance, we show the case of potato when combined with wheat, rye and rapeseed, and the case of sugar beet in an integrated farm with five other crop activities. These are important findings. Our empirical analysis shows that the welfare gain (loss) from farm diversification is determined by the choice of the outputs in the portfolio. Diversification is indeed beneficial when the gain from scope, scale and concavity components generate productivity and welfare gains. But we also show that specialized form of production can be superior for some crop combinations. This finding contributes to the existing discussion on specialization, diversification, productivity and risk mitigation issues in agriculture and is especially relevant in rural development policy making. Finally, our empirical research has focused on crops. It did not consider the role of livestock and of the non-farm sector. Further research is needed to explore these issues.

# 8. Conclusions, policy implications and suggestions for research

This chapter presents the conclusions based on the key findings and their policy implications, and it ends by suggesting areas for future empirical research.

## I. Conclusions and policy implications

This dissertation presents empirical findings on the economics of production in agriculture with a particular emphasis on employment, agricultural risk and risk management, productivity and welfare.

Chapter 3 illustrates the relationship between decent rural employment and agricultural production efficiency. Decent employment is a crucial element of quality of life. Empirical works in the manufacturing and service sectors show that decent employment can contribute to labor productivity improvements (Bloom et al., 2009; Bloom and Van Reenen, 2006). An empirical question here is if decent rural employment can help to improve agricultural productivity. We follow the ILO definition of "Decent Work Agenda" comprising key dimensions of quality of work (e.g. better working environment, health and safety conditions, abandonment of child labor, gender equality, adequate provision of social protection and promotion of social dialogue etc.) (Somavia and General, 1999). According to Somavia and General (1999) and FAO (2010), decent employment is multi-dimensional, and indicators may depend on the technology, socio-economic situations, policy and environmental conditions, culture etc. Hence, adaptation of the concept of decent rural employment to local situations is an important step for the empirical analysis, and policy and strategy design in the labor market.

The study investigates the relationship between decent rural employment and agricultural production efficiency using cross-sectional data from Ethiopia and Tanzania. Out of the total four dimensions of decent rural employment popularized by the ILO and FAO (FAO, 2010), we choose three dimensions for the empirical analysis. The dimensions that we consider in the analysis are: the proportion of household members involved in a productive work (pillar one: creation of productive employment), government transfers through different programs (pillar two: social protection), child labor and precarious forms of employment (pillar three: standards and rights at work).

In the analysis, we found that decent rural employment consistently improves the production efficiency of agriculture in the two countries considered. This implies that improving the quality of work by expansion of employment opportunities, improving provision of government transfers as social protection, abolition of precarious forms of employment and child labor, etc. can improve workers' performance and agricultural productivity. As labor is often the key production input for agriculture, and it is one of the key productive resources of the poor, labor productivity improvements through decent rural employment can have substantial livelihood implications in the developing world.

This finding has a number of policy implications for rural development and agriculture. First, this empirical finding calls for the promotion of decent rural employment in order to improve productivity and farm income for family farms. Promoting decent rural employment, by expanding paid job opportunities and improving the quality of existing ones, can play an important role in improving the productivity of agriculture in the developing world. An important area to this end is the role of farmers and farm managers. Farmers can improve labor productivity and farm income through decent rural employment. This is particularly relevant when farms face labor shortage, and provide employment opportunities. Decent rural employment is not only an important aspect of quality of life, but also can improve workers' productivity. Hence, such a win-win scenario from decent employment for both farm managers (through productivity gains) and farm employees (through better pay, quality of life etc.) can bring substantial improvement for the sector and peoples' livelihood. An important question here could be how big is the potential of small farms in terms of providing employment, and how far can we improve the decency of the work in small farms. It is true that most smallholder farms use family labor for agricultural activities. However, they also provide employment for the growing young and landless population in rural areas of SSA. Additionally, there are efforts to promote innovation and value addition in agriculture in many countries. Such changes in the innovation and improvement in the participation of farms along the value chain is expected to increase farms' labor demand. In the process, promoting decent rural employment can have stronger implication for productivity and social wellbeing.

Second, some of the dimensions of decent rural employment require strong engagement and push by policy. The full participation of the governments is crucial in shaping regulatory frameworks so as to improve the working environment and develop the labor market. Among the most important areas of intervention, improvements in standards and rights at work (water and sanitation facilities, temperature condition, clothing etc.), provision of social protection (insurances, old age pensions etc.), abolition of precarious work and job discrimination require governments' effort and commitment. Determination of minimum wage could also be an important aspect of a policy. Similarly, regulations and policies are vital to follow implementation in the labor market. The adaptation of the decent rural employment concept to local situations, and its integration with the general economic, social and other development policies is vital. What is equally relevant in this respect is the role of different stakeholders to promote the idea of decent rural employment, its contribution for farm productivity and as a key aspect of quality of life. This may include awareness creation moves on decent rural employment concepts, small-scale demonstration of social protection elements, delivery of skill based trainings to unskilled labor in the job market etc.

In chapter 4, we present empirical evidence on the relationship between the cost of risk and income diversification. Climate change is among these major challenges that limit the potential of agriculture to feed the growing population. Past evidences and climate projections show that climate change can suppress agricultural productivity, and can have disastrous livelihood consequences (Barrios et al., 2008; Intergovernmental Panel on Climate Change, 2007). Hence, farms are in a continuous adjustment to reduce the disastrous impacts of climate change.

There are a number of risk management strategies that farmers employ, and these strategies can be broadly classified as ex-ante and ex-post. Examples of these risk management strategies include soil and water conservation, irrigation, farm and income portfolio diversification, insurance, futures and commodity markets, as well as community based risk sharing etc. (Chavas and Di Falco, 2012; Di Falco and Bulte, 2013; Groom et al., 2008; Zuo et al., 2014). Ex-ante farm-based risk management strategies are especially relevant in countries like Ethiopia, where market based risk management strategies including insurance are not well-developed to give adequate protection to yield and income shocks from climate, pest and price volatilities.

Farm diversification is among the ex-ante risk management strategies in agriculture. Using repeated cross-sectional data from Ethiopia, we analyze the relationship between the cost of risk and farm diversification in smallholder agriculture. It is widely known that the severity of the risky event, the probability of occurrence of a risky event, and adaptation capacity are essential determinates of the impact of risk. Following moment based approach (Antle, 1983), we estimate the cost of risk (also called risk premium) in agriculture from the first three empirical moments of the profit distribution. Risk premium is the amount of money farmers are willing to give up in order to eliminate risk (Pratt, 1964). This can also be interpreted as farmers' willingness to pay for risk mitigation strategies including insurance.

In the analysis, we found that farmers in Ethiopia are risk averse, as most smallholder farmers elsewhere in the world. The empirical analysis confirms that the risk premium constitutes a substantial portion of the expected average income of farms. Furthermore, we show that farms that experience higher cost of risk have a larger propensity to engage in diversified income generation activities. This implies that the cost of risk (expressed by the calculated risk premium from higher level profit moments) explains part of the puzzle towards income diversification in Ethiopia.

This evidence confirming the relationship between cost of risk and livelihood diversification decisions in smallholder agriculture has important policy implications. First, this empirical evidence suggests that efforts can benefit from the progressive integration of the issue of risk towards rural development policies and strategies in the developing world. Farmers often choose to diversify to mitigate risk despite the fact that diversification might not be their choice in terms of productivity and profit maximization.

From a risk management perspective, diversification is an issue of distributing productive resources to different production activities with differences in the probability and likely impact of risk. This decision usually relies on the assumption of incorporating activities in the farm portfolio that assure a certain return, and this often is less than the maximum possible profit. The choices that farmers made to diversify to less productive farm activities with the expense of possible productivity gains from specialized agriculture can have severe livelihood implications. This is especially crucial when farmers overestimate the probability of occurrence or severity of risk, and this can lead to overprotection. Hence, timely and accurate information on the occurrence and severity of climatic events is essential. Conversely, underestimation of the cost of risk and sub-optimal investment for risk management can have disastrous consequences. Accordingly, it is recommended to integrate risk in rural development strategies in order to promote the efficiency of adoption of production enhancing technologies and practices.

Second, this finding can be an important input for attempts towards specialization in order to improve agricultural productivity. Few years back, Ethiopia has introduced a huge agricultural transformation plan as an essential part of the economic development strategy, and this largely focuses on improving the productivity of agriculture. Attempts that aim to encourage farmers to make optimal decisions with an uncertain environment requires provision of functional market and non-market based risk mitigation strategies. For instance, if the transformation plan aimed to encourage farmers to move to specialized farm enterprises, risk management should be a key area for the country to focus on.

Third, this study further confirms that the cost of risk explains a substantial proportion of profit. This amount can be broadly interpreted as the amount of money farmers are willing to give up to avoid risk. Agricultural insurance is often nonexistent in most developing countries, and when it exists, it is poorly developed and inefficient in providing complete protection against shocks. There are some efforts to introduce agricultural insurance markets in Ethiopia and the developing world, and their performance is often a function of behavioral, socio-economic, institutional, historic and political situations in those countries. Hence, provision of timely, affordable and efficient insurance market is vital in facilitating optimal agricultural production and investment decisions in the developing world.

Chapter 5 investigates the relationship between risk exposure, climate variabilities, crop diversification, insurance and investment decisions in Germany. Climate change is inherent in agriculture, and it has implications on farm decisions. As discussed, how series the effect is determined by the adaptive capacity of farms (Chavas and Di Falco, 2012; Kassie et al., 2015b). Crop diversification and insurance policies are among the widely used risk mitigation tools in agriculture (Hardaker et al., 2004; OECD, 2009). Risk exposure and climate variabilities can have investment and disinvestment implications. Alem et al. (2010) produced evidence on the impact of rainfall variabilities on fertilizer purchase decisions in Ethiopia. This can either be related to post-disaster income stress in smallholder farms, or little productivity incentive of application of fertilizer at times of shortage of water.

Existing empirical evidences are inclined to discuss the adoption and impact of one risk mitigation tool, and when they are discussed together, the possible relationship between each other is largely overlooked. Nonetheless, the possible complementarity and substitution between risk mitigation instruments (e.g. farm-based or market based), is particularly crucial for the farm manager. For instance, the possibility of using non-farm business as risk mitigation tool is largely dependent on the difference in the response to a shock with agricultural activities. An empirical paper by Rijkers and Söderbom (2013) reported that the returns of non-farm business and agricultural production co-vary at times of shock in Ethiopia. In such a situation, non-farm business can have little or no contribution for risk mitigation. De Mey et al. (2016) also highlight the application of the risk balancing concept (business risk, farm risk and off-farm risk) in Swiss farm households. Analyzing the relationship between risk management strategies (crop diversification, insurance) and investment decisions is an empirical concern we explore in chapter five.

For the empirical analysis, we use an unbalanced panel data of farms (1989-2009) together with weather data from Germany. Using a stochastic production function framework, we calculate the first moment (mean), second moment (variance) and third moment (skewness) of profit. Afterwards, we investigate the effects of risk exposure (second and third empirical moments) and climate variabilities on crop diversification, purchase of insurance policies and input expenditure. In addition, we analyze the interrelationship between crop diversification, purchase of insurance and input expenditure in a 3SLS and IV GMM framework.

The results show that arable farms with higher variance and downside risk in the preceding years are highly likely to diversify their crop production activities in sample farms. In addition, higher variance and skewness are related to higher propensity of purchasing insurance. This in other words means that risk exposure of arable farms in the preceding years is associated with higher likelihood of diversifying farm activities and purchasing of insurance policies. This result implies that farms consider crop diversification and insurance as important strategies to mitigate risk in agriculture.

The empirical analysis also shows that farms that experience higher farm profit variability and downside risk in the preceding production year are likely to invest less for farm inputs. Conversely, farms that experience positive shocks in their profit (lower variance and lower downside risk) in the preceding production season are likely to invest more for input related expenses. This result confirms the research hypothesis that risk exposure is likely to determine the propensity to invest in the farm at least in the short run.

In the analysis, we show that climatic variables are essential elements of the farm diversification, insurance purchase and investment decisions in agriculture. We confirm that annual precipitation do significantly influence crop diversification, purchase of insurance and input expenditure decisions in Germany. Similarly, sunshine hours play a vital role to determine purchase of insurance and input expenses. Mean annual temperature do also significantly influence crop diversification decisions. This implies that climate variabilities do play an important role in shaping adaptation and (dis)investment decisions on arable farms in Germany.

Another important finding in this chapter is that crop diversification, purchase of insurance and input expenditure decisions are found to be interdependent of each other. The relationship between crop diversification and insurance purchase implies that farms invest in market based risk mitigation instruments at times when farm based risk mitigation instruments can't provide full protection against risk. With this empirical evidence, we may question the existing belief on the substitutability of farm level and market based risk mitigation instruments. Diversified farms payoff especially when agricultural (or climate) risk has varied inter-crop effects (Lin, 2011). Nonetheless, farm diversification might not give complete protection against agricultural risk (Bradshaw et al., 2004; Cafiero et al., 2007). As shown in the analysis, farms also use insurance to protect themselves against risk. Hence, the finding indicates that crop diversification and agricultural insurance work together to give protection against risk, and might not be completely substitutable.

This finding has several policy implications. First, the analysis confirms that farm diversification and insurance are interdependent of each other, and seem to work together in arable farms to mitigate the pervasive impacts of risk. The sample shows no complete specialization, and these arable farms are diversified at least to a certain extent. Starting in the early 2000s, there has been a trend of increasing reliance on the insurance market. As these strategies seem not to be completely substitutable, this evidence can be used to support the discussion of improving the availability and performance of market based instruments to improve the adaptive capacity of farms. Incomplete protection of either of the risk mitigation schemes can be a reason that promote the adoption of both of the risk management schemes, and we question the existing belief on the complete substitutability of farm level and market based risk mitigation instruments.

Second, the empirical analysis shows that risk exposure and climate variabilities are substantially associated with farm diversification, insurance purchase and investment decisions. Common Agricultural Policy (CAP) pillars and strategies in the EU and Germany (e.g. rural development or greening) that aim to promote sustainable agricultural production need to integrate the possible implications of climate risk.

Third, higher risk exposure (expressed with higher profit variance and downside risk) is likely to affect adaptation and hamper investment in agriculture. This implies that risk is an important concern that determines adaptation decisions and investment decisions, and due consideration should be given to strategies that aim to reduce the costs of risk and improve welfare of farms. Improving the adaptive capacity of farms might not only give protection from the pervasive impacts of risk exposure, but also can influence their investment and disinvestment behavior.

Chapter six presents the relationship between social capital and income diversification under climate uncertainties in Ethiopia. Climate change is a serious threat to Ethiopian agriculture. Social capital is one of the risk mitigation instrument in smallholder agriculture. Social capital can give protection against idiosyncratic shocks, and it is quite common to see that those who face shocks can get protection (through cash and in-kind transfers, temporary migration of members of the household etc.) from members of the network. However, this is not theoretically possible for non-idiosyncratic (covariate) shocks. In covariate shocks, a significant proportion (or all) of the network members can face similar shocks. An example of such a situation is catastrophic event with climate change, and the empirical question is whether social capital can provide protection under such circumstances.

Recent papers attempt to investigate the implication of social capital on the adoption of risk mitigation instruments in developing countries (Di Falco and Bulte, 2013; Paul et al., 2016; Wossen et al., 2015). Di Falco and Bulte (2013) for instance document that compulsory risk sharing in Ethiopia hinders the adoption of social and water management strategies. Paul et al. (2016) indicate that social capital can have varied effects on the adoption of individual and community based risk management strategies. By controlling for the risk of climate change, we investigate the implication of social capital on income diversification in Ethiopia.

The empirical approach here is to develop a functional relationship between social capital and income diversification as a risk mitigation instrument, in an uncertain environment. The hypothesis here is the existence of substitution between social capital and income diversification. Social capital is multi-dimensional and the choice of the dimensions is an issue of concern in empirical investigations. As our analysis focused primarily on risk mitigation, we rather choose defensive dimensions of social capital that are related to the mitigation of shocks. Accordingly, we choose “Borrow“ (whether the head of the household believes that there is always someone that he/she can borrow 100 birr at hard times) and “Insurance” (whether the household is a member of at least one group-based funeral insurance scheme locally called “iddir”*)*. “Borrow” captures the level of trust of the household head on the financial support that can be obtained from the social network during hard times. “Insurance” is the socio-cultural enforced protection for the household during hard times (such as sickness, fire and livestock loss, death of family members, etc.) (Dercon et al., 2006).

For the analysis, we use a repeated cross-sectional data for Ethiopia and long-term climate records. The analysis has two components. First, we estimate the relationship between social capital and income diversification for the whole sample. Second, by classifying the sample in two according to the severity of climate change shocks, and we re-run the analysis with similar procedures. The first group comprises areas with moderate climate change impacts and, the second one consists of areas with severe climate change impacts.

The result shows that an increase in social capital leads to specialization of income generation activities of the household in Ethiopia. Conversely, rural households with lower social capital have a higher propensity to diversify their income generation activities. This implies some kind of substitution between the role of social capital and enterprise diversification towards mitigation of the negative effects of climate change. However, complete substitution between social capital and income portfolio diversification is practically impossible due to the non-idiosyncratic nature of climate change effects. By classifying the sample in to sever and moderate climate change regions, we also show that higher social capital promotes specialization. However, the effects of social capital on specialization are smaller for areas with severe climate change effects. On the other hand, social capital leads to higher level of specialization in areas with moderate climate change effects. This implies that farmers to a certain extent understand that social capital might not provide adequate protection against covariate risks (example climate change) that affect most of or the entire social network.

This finding on the relationship between social capital and risk mitigation instruments in Ethiopia has some policy implications. First, this analysis shows that social capital influences the level of income diversification. This demonstrates the behavioral choices of farmers in an uncertain production environment. The result indicates that social capital is one of the risk management strategies. The choice can either be made because it is the optimal decision for the household (e.g. compared to expensive risk management tools); or it can also be a result of the non-existing market based risk management tools.

This result can also be an important input to efforts that aim to develop the insurance market in the developing world. For instance, the existence of climate change and cost of risk cannot be fully interpreted as the willingness to pay for insurance services, as social capital can provide some protection (but an incomplete one) against shocks. It is crucial to consider the trade-offs and inter-relationships between different risk mitigation instruments to develop effective insurance market in the developing world. Furthermore, an in-depth understanding of market and non-market based risk mitigation instruments is an essential step in rural development policy and strategy formulation.

Second, we also show that the effects of social capital on specialization on one income generating activity are weaker for regions with severe climate change effects. This implies that farmers are likely to reduce their dependence on social capital for risk management on areas that are vulnerable to climate change effects. Such a difference on reliance on social capital for risk mitigation across different climate change regions might indicate possible learning. Through learning, farmers, at least to some extent, seem to understand the riskiness of using informal insurance to deal with covariate risks. This calls for the role of knowledge and learning for optimal choice in the farm.

Third, the variation on the relationship between social capital and income diversification across regions suggests the need for different policy recommendations. Some farms made sub-optimal decisions by choosing social capital as a risk management tool as social capital cannot provide protection against covariate risks. The first policy and strategy setup is for the farmers with such inappropriate choices. These intervention measures include education and awareness creation, extension and advisory services, etc. On the other hand, farmers can also depend on social capital as they are constrained by lack of resources and a nonexistent insurance market. A policy framework that incorporate provision of credit and insurance markets, improvement of the factor and product markets can be crucial for such farmers. Overall, the result calls for different policy recommendations for different groups of farmers so as to adequately target them.

Chapter seven presents the welfare implication of farm diversification using panel data of arable farms from Germany. In the last couple of decades, farms in Germany have gone through a series of technological, structural and economic transitions. The contribution of agriculture to the economy and employment drastically shrinks. Similarly, the number of farms continue to decline and farms increase in size (BMELV, 2006; European Commission, 2013; Eurostat, 2013). These changes are also followed by changes in the economic structure of farms, including changes in output specialization (or diversification). For physical and biological, climatic and socio-economical, policy and institutional reasons, farm diversification remains an important farm feature in Germany. Through the possible economies of scale, specialization is assumed to contribute to farm production efficiency in agriculture. On the other hand, farm diversification can also pay off through scope economies and jointness of production. Diversification can also be of one of the risk management strategies in agriculture.

The aim of this chapter is to evaluate the welfare implication of diversification (specialization) in agriculture. For this, we compare the certainty equivalent of completely diversified farms and partially specialized farms. The certainty equivalent of the farm constitutes of two parts: the first one is the productivity component of the farm, and the second one is the risk premium of the farm. In the calculation of certainty equivalent of farms, we follow a utility maximization framework where the farm operator is expected to maximize the certainty equivalent of the farm. For the empirical investigation, we use an unbalanced panel data of arable farms from Germany. We acquired this dataset from FADN, and the dataset consists of arable and mixed farms from 1989 to 2009.

The first step is to define the empirical relationship between agricultural inputs and outputs through a transformation function. Using a moment based approach (Antle, 1983, 1987), we calculate the first moment, second moment (variance) and third moment (skewness) of the profit distribution. The approach provides us with a framework to evaluate the productivity implications from the first moment. Similarly, the risk premium of the farm is calculated from the second and third empirical moments.

The next step is to compare the welfare of diversified and specialized farms. The difference in welfare can also be disaggregated in to: i). complementary component, ii). scale component and, iii). concavity component. A positive complementarity component in the production and risk premium components exists when synergy among outputs increases productivity and reduces the risk premium of the farm. Similarly, scale economies exist when the production technology exhibits increasing returns to scale and this provides an incentive to diversify. On the other hand, decreasing returns to scale gives an incentive to specialize in a certain production activity. Concavity is the other component in the welfare of farms. A concave production function (exhibiting diminishing marginal productivity) contributes to economies of diversification. Alternatively, a convex production function would provide a disincentive for diversification.

Using an average hypothetical farm, we then investigate the differences in productivity and risk premium of diversified and partially specialized farms. We develop four different diversification scenarios based on the experiences of existing sample farms in Germany. Under scenario S1, we compare the welfare of an integrated farm that equally allocates its land among four crops: wheat, barley, rye and rapeseed production, with the sum of welfares of each of the four partially specialized farms. Hence, a partially specialized farm produces each of these crops on 80% the cultivated land, and distributes the remaining 20% of land for the rest. Then, we do the same for scenario 2 by replacing barley by potato. Scenario S3 considers comparison of integrated and specialized farm producing five outputs (wheat, barley, rye, rape seed and potato). Finally, under scenario S4, we consider farms producing six arable crops (wheat, barley, rye, rapeseed, sugar beet, pulse).

Our results confirm positive productivity effects of diversification scenario 1 and 3, while negative productivity effects in scenario 2 and 4. This implies that, some forms of diversification are higher in productivity compared to specialized farms. On the other hand, other forms of diversification can be less productive compared to partially specialized forms of production. The incentive (disincentive) from diversification depends on the strength of gains and losses from complementarity between outputs, scale effects and concavity effects.

The empirical analysis shows that the effects of diversification on risk premium are also dependent on the type of crops included in the diversified farm. Whereas some forms of diversification give an incentive to reduce the cost of risk, other forms of diversification are even worse compared to production in partially specialized farms. This implies that diversification might not always benefit farms towards the mitigation of risk. This result deviates from the existing knowledge of the role of farm diversification as a risk management tool in agriculture. Through this empirical finding, we show that farm diversification might not reduce the cost of risk, and this is evident when crops that farmers grow have similar response to a shock. An example is a farmer diversifies in to crops with similar responses to climatic events, or crops with similar price pattern in the market. In this case, a failure in return (or yield) of one crop is less likely to be compensated with the gain from the other activity.

Our analysis also confirms a variation in the effect of diversification for the welfare of farms, to the extent that some forms of diversification is worse-off compared to partially specialized farms. The effects are again dependent on the strength of complementarity, scale and concavity components to increase productivity and reduce risk premium in diversified agriculture. This in other words mean that, the welfare effects of diversification are highly dependent on the responses of crops included in the farm portfolio.

This finding has several policy implications. First, the result indicates that productivity, risk premium and welfare effects of farm diversification are highly influenced by the type of crops included in the farm portfolio. In situations like this, the choice of crops to include in the portfolio with diversified farming is of paramount importance. In addition to individual performance of the crop to improve productivity or its resilience against shock, the interactions of the crop with other production activities is very crucial to determine the overall performance of the farm.

Second, the result showing the variation of returns of farm diversification on risk premium, has an implication for the development of the insurance market. Insurance systems often determine the costs for insurance policies based on area allocation of individual agricultural activity, and do not consider the interaction between multiple production activities. As the interdependence (complementarity or competition) of production activities in agriculture explains a major component of the variation in risk premium and productivity, it is crucial to consider this issue when determining the cost of insurance policies. Such a revision in the approach can also improve the performance of the insurance market in proving adequate services to the agriculture sector.

Third, this finding demonstrates that the returns from farm diversification substantially vary depending on the combination of farm production activities in the farm portfolio. Some forms of farm diversification are better-off in productivity and can help for risk management. Conversely, some crop activities can perform better in specialized farm. This implies that general conclusions on the productivity effects of specialization (or risk management effects of diversification) can often lead to unintended outcomes. The finding can contribute to adequately target farms in the Common Agricultural Policy (CAP) and other policies related to agricultural development. An example of such a policy could be an effort to promote biodiversity in agriculture. In some situations, a policy does not need to subsidize such an attempt when diversification pays-off in terms of welfare. On the contrary, overestimation of the risk mitigation potential of farm diversification leads to under compensation to losses through diversification. Hence, we argue that rural development policies might not bring us the intended result if they are not properly targeted, and policy formulation requires an in-depth understanding of the farming system.

**II. Suggestions for further research**

This dissertation finally raises some questions for future empirical investigations:

1. As employment opportunities and quality of jobs offered by smallholder, medium and large farms can substantially differ, it is an empirical question to investigate the implication of decent rural employment for improving productivity across different size groups. Additionally, we suggest

exploring the variation in the effects of different dimensions of decent employment on agricultural productivity.

2. The possible implication of other risk mitigation mechanisms including the non-farm sector and market based risk mitigation mechanism (e.g. insurance), either through complementarity or substitution between risk management strategies is given little attention in this dissertation, and can be an important area of research. Furthermore, we suggest exploring the relationship between risk management strategies, farm and non-farm investment, saving and consumption from the farm household perspective.

3. Social capital and income diversification seem to be substitutable, at least to a certain extent, in the mitigation of risk. However, we only emphasize on some dimensions of social capital, and its effect on income diversification. Exploring the implications of all the dimensions of social capital for the possible risk management strategies could be an important area of future research.

4. As the probability of occurrence and extent of risk can vary across regions; and climate change adaptation strategies can be different across different economic (farm) groups, we suggest an empirical investigation that explore the cost of risk and adaptation strategies across different size groups and regions.

5. Related to the welfare implications of crop diversification, we highlight only some of the possible interactions between different crop production activities in Germany. This requires an additional empirical study to explore the whole set of possible complementarities and resource competitions between farm activities either to improve productivity or reduce risk. The possible implication of diversifying outside of agriculture (non-farm employment or starting a non-farm business) remains open, and further investigation is needed.

## 9. Author contributions

1. Habtamu Yesigat Ayenew, Elisenda Estruch, Johannes Sauer, Getachew Abate-Kassa, Lena Schickramm, Peter Wobst "Decent rural employment and agricultural production efficiency: Empirical evidence from Tanzania and Ethiopia", Agricultural Economics,48(5):587-596 DOI: 10.1111/agec.12359

Habtamu Yesigat Ayenew did the literature review, performed the analysis, and wrote the paper. Elisenda Estruch, Johannes Sauer, Getachew Abate-Kassa, Lena Schickramm and Peter Wobst substantially contributed through multiple rounds of critical review and feedbacks. Christina Mack helped in data management. This study was conducted with the research grant from FAO. We would also like to thank Rob Vos, Silvio Daidone, Benjamin Davis and colleagues from the Decent Rural Employment Team of FAO for their valuable feedbacks. This article has also benefited from comments and suggestions from the participants of the 10th IZA/WB Employment and Development Conference and the 29th International Conference of Agricultural Economists. Any errors and omissions are those of the authors.

2. David Wuepper, Habtamu Yesigat Ayenew, Johannes Sauer, "Social Capital, income diversification, and climate change adaptation: Panel data evidence from rural Ethiopia" in Journal of Agricultural Economics, 69(2):458-475 DOI: 10.1111/1477-9552.12237

The first two authors, David Wuepper and Habtamu Yesigat Ayenew, have equally contributed to this article in reviewing relevant literatures, developing the concept and framework for the analysis, preparing the data for analysis, performing the analysis, and writing the article. Johannes Sauer contributed in the process from developing the concept to the write up through valuable suggestions and feedbacks and help to improve the article. We would like to thank International Food Policy Research Institute (IFPRI), Center of Economic Studies and Addis Ababa University for making the dataset available for public use. Fabian Frick and Stefan Wimmer also give valuable feedbacks to improve the draft.

3. Habtamu Yesigat Ayenew, Johannes Sauer and Getachew Abate-Kassa ( ). Farm Diversification and the Cost of Risk in Smallholder Agriculture: Panel Data Evidence from Ethiopia, under peer-review with the Environment and Development Economics Journal

Habtamu Yesigat Ayenew developed the concept, did the literature review, performed the analysis, and wrote the paper. Johannes Sauer substantially contributed for development of the concept, analytical procedure, and critical reviews. Getachew Abate-Kassa contributed through multiple rounds of review and feedbacks. This chapter has also benefited from the participants of the 89$^{th}$ Agricultural Economics Society (AES) in Warwick, UK. We would like to thank International Food Policy Research Institute (IFPRI), Center of Economic Studies and Addis Ababa University for making the dataset available for public use.

4. Habtamu Yesigat Ayenew, Johannes Sauer and Getachew Abate-Kassa ( ). Risk exposure, climate Variability, Adaptation and Farm Disinvestment in Germany, under peer-review with the Environmental and Resource Economics Journal

Habtamu Yesigat Ayenew developed the concept, did the literature review, performed the analysis, and wrote the paper. Johannes Sauer substantially contributed for development of the concept, analytical procedure, and provide critical reviews and suggestions. Getachew Abate-Kassa contributed through multiple rounds of review and feedbacks. This chapter has also benefited from the participants of the 89$^{th}$ Agricultural Economics Society (AES) in Warwick, UK.

5. Habtamu Yesigat Ayenew, Jean-Paul Chavas, Johannes Sauer ( ). Farm diversification, risk and productivity: Evidence from arable farms from Germany, under peer-review with the Agricultural Economics Journal

Habtamu Yesigat Ayenew developed the concept, did the literature review, performed the analysis, and wrote the paper. Jean-Paul Chavas substantially contributed to the development of the concept, analysis, and writing the article. Johannes Sauer contributed by providing critical reviews and suggestions. The paper was written when Habtamu Yesigat Ayenew had a research stay at the University of Wisconsin Madison, under the supervision of Prof. Jean Paul Chavas from August-October 2016.

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