A dissertation on

Aspects of demand-side oriented insurance of volatile food prices in developing and emerging countries

(Aspekte der nachfrageseitigen Versicherung volatiler Nahrungsmittelpreise in Entwicklungs- und Schwellenländern)

by

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List of Abbreviations

LDC	Least developed countries
IFLS	Indonesian Family Life Survey
PD	Poverty deficit
GDP	Gross domestic product
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
INR	Indian Rupees
OLS	Ordinary least squares
AME	Average marginal effect
DVfVW	Deutscher Verein für Versicherungswissenschaft
ILO	International Labor Office
IFPRI	International Food Policy Research Institute

1 General Introduction

A friend of ours from the world of high finance always says that the poor are like hedge-fund managers – they live with huge amounts of risk. […] In fact, he grossly understates the case: No hedge-fund manager is liable for 100 percent of his losses, unlike almost every small business owner and small farmer.

(Banerjee and Duflo, 2012, p. 134f)

Drought events in different parts of the world create impressive images and attract the attention of the media, politicians and the public on the vulnerability of livelihoods in agrarian economies of least developed countries (LDC). While images of dried up landscapes, perished animals and undernourished humans are an effective instrument to create public awareness, they are usually the most extreme manifestation of rainfall risks. But even if the magnitude of realized rainfall volatility is smaller, it does not mean that income related to agriculture was secure. As the agricultural activity of small-scale farmers in LDCs is mostly rainfed, the correct timing and amount of seasonal rainfalls is of decisive importance for crop yields and income generating activities linked to harvest amounts. Thus, even comparably small deviations in rainfall realizations or in the timing of cyclical rainfalls may induce income losses although they neither have the potential to create shocking images and news nor to attract public awareness or to trigger relief payments or charity events.

During the years 2008-09 and the global food price crisis, the developed world learned about a new source of income risks, when outraged people revolted against rising food prices, for instance in Bangladesh, Somalia, Egypt or Senegal. Several people got injured or even killed when overstressed governments intervened in protests and riots against rising staple food prices. While the reasons for increasing prices are still subject to ongoing discussions, the consequences were particularly felt by the poorest parts of the population who saw their incomes getting devaluated. Moreover, as agricultural input prices for seeds and fertilizer rose at the same time, farmers had to economize, releasing millions of day laborers into unemployment or forcing them to accept wage cuts (Banerjee and Duflo, 2012). Food price variability and increasing food prices impact on the food security situation of households in a negative way. The term food security has been defined by the World Food Summit in 1996 in the following way:

> *Food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life.*
>
> (Food and Agriculture Organization, 2006)

Food security comprises different dimensions such as food availability, food utilization, food stability and food access. The first dimension of food security covers the aspect of physical availability of food, which is ensured by domestic production, imports or even food aid. While the utilization dimension of food security is concerned with other food related components such as access to clean water, sanitation and health care, food prices increases and rainfall variability are particular threats to the stability and access dimension of food security. Food security is only reached if every household has permanent access to sufficient amounts of food and micronutrients. However, if food prices are variable and increase for any reason, this may exclude certain households from consuming sufficient amounts of food and micronutrients and thus violates the above given definition of food security. Rainfall shocks and their effect on agricultural production are a threat to the stability as well as the availability dimension. Lacking rainfall has the potential to destroy crops and harvests but may also have an effect on food prices if the supply of food decreases in the aftermath of a rainfall shock. Thus, protesting individuals in countries with rising food prices saw their food security situation to degrade.

These perspectives on two risk types of the recent past illustrate the fragility of livelihoods in LDCs in general. Furthermore, they illustrate the constant need to manage the risks of low income households in LDCs every day, even if risk realizations are not that severe that they attract public attention or relief payments. Hence, this dissertation is aimed to shed light on the position of low income "hedge-fund managers" and the two dimensions of possible risk management decisions taken by them: informal and formal practices. Confronted with lacking public safety nets, imperfect access to capital markets and weak institutions but also pronounced income risks, informal risk management is at the center of risk provision. From a farmer's perspective this could mean to plant a variety of differently drought-prone crops or to split up labor time over different income generating activities, i.e. farming and supplying time to labor markets. Informal risk management may also comprise selling assets, strategic migration or school dropouts of dependents. For most of these strategies, disadvantages outweigh advantages: Diversifying the set of crops planted could mean to lower the production risk but at the same time to lower the expected yield and thus income. In this perspective, production risk may contribute to the chronification of poverty as producers may be trapped in "low risk-low yield" production plans. A similar criticism is made towards asset-based strategies such as selling assets in times of distress or taking children out of school: Depleting a household's capital stock or decreasing the investment into it decreases future earning possibilities and may thus also lead to perpetuating poverty structures. In addition, asset based income smoothing turns out to be ineffective when the number of households willing to sell assets during times of distress is high while the number of asset-buying counterparts is low. This creates a downward pressure on asset prices and deteriorates their income smoothing power. With respect to labor time allocation, splitting up the labor time potential may mean to decrease the degree of specialization and, as it will be argued in chapter 2, changes the composition of income risk when consumption prices are uncertain and volatile while the overall income risk decreases less than expected.

The weaknesses and potentially negative side effects of informal risk management have triggered the development of formal risk transfer instruments such as microinsurance. In a first attempt to define the term microinsurance, Churchill (2006) writes:

> *Microinsurance is the protection of low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved. This definition is essentially the same as one might use for regular insurance except for the clearly prescribed target market: low-income people. How poor do people have to be for their insurance protection to be considered micro? The answer varies by country, but generally microinsurance is for persons ignored by mainstream commercial and social insurance schemes, persons who have not had access to appropriate products.*
>
> (Churchill, 2006, p. 12)

Although this definition has been elaborated and broadened in the meantime (Churchill and McCord, 2012), it clearly shows the similarities with conventional insurance. As premiums and conditions are also adapted to the target group, underwriting and claims settlement processes have to be designed in the most cost effective way to guarantee the affordability for the target group of low income households.

In the attempt to insure systemic income risks in agrarian economics in a cost effective way, risk transfer markets have seen the development of index-based microinsurance products. While microinsurance policies resemble conventional insurance products in particular with respect to the determination of indemnity payments, index based microinsurance works differently. Its main characteristic is that indemnity payments are not contingent on on-site damage and loss assessments but rather they are triggered when predefined threshold levels of non-influenceable index variables were exceeded. For instance, an index-based drought insurance policy would trigger indemnity payments to insured farmers only whenever the amount of rainfall at a predefined rainfall gauge in a predefined period of time was below the rainfall threshold at which healthy crop growth is sufficiently likely. This indirect loss assessment reduces moral hazard incentives as well as it allows insurers to insure a large set of households in a cost effective way. However, the particularities in product design raise other issues. For instance, it is widely reported that the demand for these products stays behind expectations and that lacking demand can be explained by –among others– skepticism about the product but also by product inherent characteristics (Awel and Azomahou, 2015, Karlan et al., 2014, Cole et al., 2013, Norton et al., 2011, Hill and Robles, 2011, Giné et al., 2010, Giné and Yang, 2009).

Hence, the structure of this dissertation should be straightforward: In order to assess the magnitude of rainfall and food price volatility induced income variability, Chapter 2 will review empirical evidence on induced welfare effects by the two risk types. Household level outcomes will be categorized along the measurement variables such as income changes, effects on poverty measures or consumption changes. The analysis has no specific geographical focus. However, as the dissertation is on formal and informal risk management in LDCs, studies from developing and emerging countries in south-east Asia, Latin and South America as well as Africa have been selected for the review. In a second step, evidence on the extent of informal risk management strategies with a particular emphasis on labor related strategies will be reviewed. This means that the evidence on informal adaptations using child labor, the coping power of labor markets and consumption responses will constitute the main analysis elements in the risk coping section.

In chapter 3, informal risk management practices with a particular emphasis on labor time allocation stand in the focus of the analysis. It is argued that splitting up the labor time potential over different income generating activities to cope with rainfall variability does not lower the overall income risk to the extent which an household had hoped for. This argumentation is mainly linked to the observation that consumption prices for staple foods are variable and rainfall patterns are not completely predictable. Hence when households split up their labor time potential, they diversify their rainfall induced production risk. Due to food price variability, these households tap into a purchasing power risk if their wage income is devaluated by increasing food prices. Hence, if rainfall and food price variability are imperfectly correlated, the overall income risk decreases by splitting up the labor time potential. However, the diversification effect is reduced due to food price volatility and the resulting purchasing power risk. Using a household data set from India, it will then be tested to which extent the labor time allocation depends on the magnitude of income risks, i.e. food price and rainfall variability.

In chapter 4, the relation between informal and formal risk provision will be tested. By using demand data for an index-based drought insurance product from India, the demand function for the product will be estimated subject to the degree of informal risk management, again modelled by the degree of labor time allocation. It is hypothesized that the degree of informal risk management provides a certain degree of informal income protection. Hence, those who have a more diversified income portfolio and perceive relatively higher income shares from non-rainfall dependent activities have a lower incentive to buy an insurance product which insures them against rainfall variability. Hence, it is empirically tested whether the degree of informal risk management has a negative effect on formal insurance demand such that informal and formal risk management strategies stand in concurrence to each other. Chapter 5 will conclude the dissertation with a general summary.

2 Risk and risk coping in least developed countries: A review of drought and food price risk effects

Abstract

Many studies in the recent past have been published to quantify poverty effects of realized income risk such as drought events or the consequences of the recent global food price crisis. As agrarian economies in least developed countries heavily depend on the correct onset and amount of rainfall quantities, lack of rainfall is likely to have adverse consequences for household income and its volatility. In addition, agrarian households in least developed countries are mostly net food consumers and thus highly dependent on the realization of food prices. This study reviews the empirical evidence on adverse income effects of drought events and food price increases as well as it summarizes the risk management and coping strategies directly linked to these two shock types. A particular emphasis will be given to the stabilizing power of labor markets and adaptation through consumption responses.

2.1 Introduction

Risk is an omnipresent phenomenon in agrarian economies. Rainfed production is constantly threatened by rainfall variability such as lacking or excessive rainfall. In a perfect theoretical world with universal access to capital and insurance markets, households would be able to trade their income risks and could thereby flatten their consumption profiles. As capital markets in developing and emerging countries, however, are marked by unequal access and imperfection, transferring risks is not always possible. In the light of this complication, households are forced to manage their risks using informal and formal strategies. Some of them are applied in an *ex ante* manner, some of are used to cope with the risks *ex post*. The riskiness in income profiles is not only induced by rainfall variability. Agricultural outputs are marketed at goods markets to use the profit for consumption purposes. As most producers are also net buyers of staple foods, price changes for agricultural goods are likely to affect their position as a seller but also as a consumer of food (Minten and Barrett, 2008, Poulton et al., 2006).

The purpose of this chapter is twofold. With regards to the first, empirical studies that quantify welfare effects induced by drought events as well as potential welfare effects from changing yet increasing food prices are reviewed. The second aim of the study is to review studies that address the informal risk management decisions of households, aimed to mitigate the income shocks induced by drought and food price shock events. In order to address the second purpose of the study, the main emphasis will be on the risk mitigating power of labor markets, drawing on studies estimating the extent to which labor time allocation but also the extent to which child labor is used to cope with shock events. The review leaves out studies considering welfare effects induced by climate change induced gradual losses. The reasoning for that is that climate change impacts on weather patterns in two ways: First, it makes extreme weather events more likely and also more frequent. Second, climate change also contributes to long lasting changes for instance increasing average temperatures. The review, however, draws on risks that are potentially insurable on a competitive insurance market to research a household's decision between informal and formal risk management and coping activities. Climate change induced gradual risks and losses are uninsurable by any kind of insurance policy supplied by competitive insurance markets. Hence, even though households have to deal with gradual losses, they do not induce a rivalry between informal and formal risk management as only informal activity is available in this case.

Risk and risk coping in developing and emerging countries as well as coping strategies were subject to previous survey articles. Dercon (2002) uses a broader risk notion by including idiosyncratic as well as systemic risks into the review. He also reviews evidence with respect to the effectiveness of informal risk management strategies. He concludes that the effectiveness of an applied strategy will depend on the shock character, on the ability to bear entry costs of these strategies as well as on the income position held prior to shock materialization.

Dorward (2012) provides an overview of theoretical and empirical papers to assess the impact of changing food prices for consumers and producers in developing and emerging countries. His main insights are that increasing staple prices had heterogeneous effects for different types of market participants. All in all, poor urban and rural net buyers of food were the ones most affected by rising food prices while he negates the hypothesis of positive second round effects, i.e. through rising wages or adapted production plans. Heterogeneity in food price increase effects is also driven by the degree of price transmissions from international into domestic markets where he concludes that some countries are better shielded than others.

As there was a significant development in the literature on quantifying welfare effects of surging food prices and consumption responses as well as on child labor responses after 2012, it is appropriate to systematize studies dealing with these aspects of risk and informal risk management in developing and emerging countries. Nevertheless, studies published before 2012 will also be included to show the evolution in the argumentation. The search algorithm for studies included in this review considered mostly empirical papers published since the year 2000 in peer-reviewed journals while the impact factor of a respective journal was not a choice criterion. A backward search has been applied by working through the references of a respective paper while forward search has been conducted using the citation function of Google Scholar. Other bibliographic databases have not been included in the literature study. There was no explicit geographical focus except for the fact that only studies on developing and emerging countries in Latin and South America, Africa and Southeast Asia were included in the review.

The structure of the paper is as follows: In section 2.2, studies quantifying income effects from drought events and food price shocks will be reviewed and systematized according to the variable welfare changes have been measured with. Section 2.3 will review studies estimating the impact of food price volatility on household welfare measures. In section 2.4, risk management as well as coping strategies will be reviewed with a particular focus on labor market related strategies and approaches. Section 2.5 will conclude and wrap up the main insights and implications.

2.2 Impact of rainfall induced shocks on households

The following section will review empirical studies quantifying the extent of systemic shocks on outcomes at the household or macroeconomic level. Systemic shocks comprise rainfall induced shocks such as droughts or flood events. Furthermore, systemic shocks will also comprise potential income effects induced by food price volatility. Effects from shock events at the household level were measured in different outcome variables such as income and expenditure effects and changes of the latter, poverty measures such as poverty threshold or headcount estimations and measures of food security.

2.2.1 Rainfall risk induced expenditure effects

Many scholars attempt welfare effects from weather disturbances by measuring their effect on consumption, consumption growth or expenditures. This review distinguishes between expenditure and income effects, although these two measures are closely related. However, the quantification of expenditure effects reveals redistribution of expenditures which is of interest and will therefore be separated from pure income effects.

Dercon (2004) analyses the effect of drought shocks on consumption growth using a panel data set comprising the period from 1989 to 1997 in six villages in rural Ethiopia. Almost all individuals in the sample have access to land and therefore depend on agriculture and rainfall outcomes. He finds that a 10% decrease in rainfalls leads to a reduction of food consumption growth of about 5 % and equivalently to a 3% reduction in total consumption.

The magnitude of shocks is not uniformly distributed among population groups and may change in sociodemographic but also geographical variables (Skoufias and Vinha, 2013, Skoufias et al., 2012, Dercon et al., 2005). According to Dercon et al. (2005), drought shocks reduce per capita consumption – including food and non-food items – by about 19 % on average. By further disseminating shock effects according to household characteristics, they find that female-headed households experience a 43 % decrease in per capita consumption while male-headed households cut per capita consumption levels by about 10 %. In addition, households with low head of household education levels experience a 20 % reduction in per capita consumption while households with better educated head of households incur a 14 % reduction in the same number. It is questionable whether this finding represents a causal relationship. However, it seems to be reasonable that more educated households have more abilities to spread their labor force to employment besides agriculture. In consequence, better educated households may have a less rain sensitive income portfolio. Skoufias and Vinha (2013) find that the protection of consumption levels depends crucially on the geographical location of the respective household: Households living in dry areas are less able to protect their consumption from rainfall and temperature shocks compared to individuals living in sub-humid and humid areas of the country. In addition, it is crucial at which point in the agricultural year a rain or temperature anomaly has been experienced.

The study of Skoufias et al. (2012) analyzes the effect of rainfall shocks on total real per capita expenditures on food and non-food components in Indonesia. In their sample, rice is the primary production good and susceptible to variations in rainfall. They model rainfall shocks as the difference in days after which cumulative rainfalls exceed 20 mm after August 1 of a respective year and the day when the critical threshold has typically been reached. This is what the authors call 'onset' of the monsoon. The main result is that an onset delay of one standard deviation reduces real per capita food expenditures by about 13 %. By further differentiating the analysis, they find that specialized rice farmers suffer even more from rainfall variability: An increase in the severity of a post-onset drought reduces the non-food expenditures of rice farmers by 25 % whereas food expenditures decrease insignificantly. Skoufias et al. (2012) conclude that rice farmers are able to protect food consumption by decreasing the level of non-food expenditures.

Other studies find that that the magnitude of income drops depends on the severity of rainfall shocks, such as Porter (2012) by analyzing a sample from the *Ethiopian Rural Household Survey*. She finds that real household monthly consumption –including food and non-food items– dropped between 7 and 25 % for villages where actual rainfalls were in the bottom quintile of the 30-year rainfall distribution, compared to villages where actual rainfall was in the third quintile.

Arouri et al. (2015) assess the impact of floods and droughts on households using a panel data set from Vietnam. Their major variables of interest were per capita income and per capita expenditures. Using a community level fixed-effect model, they found that the occurrence of a drought reduces per capita income by about 6 %, whereas a flood reduces the same by about 5 %. A similar effect size is found with respect to per capita expenditures which decreased by around 4 % following a flood or drought event.

Other scholars draw research on potential shock mitigating effects induced by public assistance programs. Hill and Porter (2017) conduct an analysis on the consumption effects of droughts and other kinds of shocks in Ethiopia. They use two waves of rural household surveys from the years 2005 and 2011, containing information on self-reported idiosyncratic shocks by the households surveyed whereas information on covariate shocks were exogenously collected and matched according to the geographical reference of the respective households. The authors estimate a consumption function, where the total expenditures on food and non-food per adult equivalent have been used as the dependent variable. Drought damages were measured in the proportion of crops lost using the *Livelihoods, Early Assessment and Protection* forecasts. It is found that a 10 % increase in crops lost leads to a 3 % reduction in adult equivalent consumption levels of the households under study. This number decreased slightly to 2 % if the household was supported by the *Productive Safety Net Program*, introduced in 2005. The authors explain the small difference between the two groups of households by the fact that the 2011 drought in Ethiopia was comparably less severe than other drought events.

2.2.2 Rainfall risk induced income effects

The previous section presented empirical evidence for rainfall shocks impacting on expenditure structures of households. The following section will review the evidence of rainfall shock induced income effects.

Molua (2011) explores the effect of weather uncertainty on expected farm profits in Cameroon, differentiating for potential gender related effects with respect to farm ownership. Rainfall uncertainty decreases expected profits of both male and female owned farms. However, female owned farms are more strongly affected by rainfall variations, which decrease expected farm profits by up to 15 % while male owned farms see their profits to decrease by up to 14 %. At the same time, the author finds that rainfall variability increases the farm profit variability by up to 38 % for female and up to 31 % for male owned farms.

Porter (2012) further analysis the impact of rainfall shocks on crop income. In her sample, the average crop income share is relatively high. In 2004, 66 % of household income stems from selling crops. Consequently, if actual rainfall levels were in the bottom quintile of the 30-year rainfall distribution, this reduced crop income by 17 % compared to farmers residing in villages where actual rainfall fell in the third quintile of the long-term rainfall distribution.

As growing and selling crops is the most important income source in most of the developing countries, production is not only susceptible to changes in rainfall levels but also with respect to temperature variability. Thiede and Gray (2017) look into the effects induced by temperature anomalies and delayed onset of the monsoon on the composition of household incomes. The study uses data from the *Indonesian Family Life Survey (IFLS)* of the waves 2000 and 2007-08, containing individuals from 15 to 49 years of age. Income data was collected during the 12 months prior to each survey. A marginal deviation of the long-term temperature mean results in a 1.67 units decrease in farm profits, whereas farm profits stay unaffected from a delay in the onset of monsoon rainfalls. The same result holds for other income sources such as non-farm business revenues or non-agricultural labor.

Generally, it is found that the strength of the income effect may also be affected by socio-demographic variables. This result was also found when the variable of interest was household expenditures. However, the magnitude of income cuts seems to be more pronounced than expenditure cuts, emphasizing the importance of expenditure reallocation as a risk coping strategy.

While the majority of scholars were concerned with the microeconomic outcomes of rainfall variability, there is also evidence on the macroeconomic level. Pandey et al. (2007) use a cross-country study to estimate the economic costs[1] induced by a drought for southern China, eastern India and northeast Thailand. They find that India is hit hardest by drought events with economic costs amounting to $856 million per drought event and $85 and $133 million for Thailand and China respectively. The authors further estimated that drought events resulted in a 24-58 % reduction in overall income, where average crop income reduced from $600 in normal years to $90 in drought years in Chattisgarh, in northeastern India for instance.

[1] Pandey et al. (2007) use a broad notion of economic cost including direct costs such as losses in harvest amounts but also opportunity costs that arise due to a loss in specialization induced by informal risk management of drought risks.

2.2.3 Rainfall risk induced food security effects

A different approach to measure the impact from rainfall variability on household outcomes is to look at measures of food security or malnutrition as a consequence of shocks. Considering measures of food security allows analyzing the intra-household distribution of food during periods of distress. For instance, Hoddinott and Kinsey (2001) explore the effect of a drought on child growth in Zimbabwe. They use growth rates of child height and regress them on structural and shock variables. Their main insight is that a drought experience slows down the child growth rate in particular for children aged between 12 and 24 months at the time of drought occurrence.

Support for malnutrition induced causality is found by their robustness analysis which finds that the reduction in child growth is smaller among asset rich compared to asset poor families. Thus, they provide evidence that rainfall shortages translate into declining provision of adequate food and nutrients. Several studies find a positive relationship between child growth and subsequent outcomes, i.e. taller adults earn more in later years (Schultz, 2003, Thomas and Strauss, 1997). Thus, drought experiences in younger years may have long lasting effects on future earnings and poverty outcomes.

Generoso (2015) estimates the probability of switching between different categories of food security depending on the occurrence of inter-annual rainfall fluctuations. Households are matched to the different food security categories by rating the dietary diversity and economic access to food. Using a household survey from Mali, he finds that an increase in the inter-annual rainfall variability increases the likelihood to switch from the highest to the lowest food security-category by about 38 % in the Sahelian zone of Mali. The effect is less pronounced in the Sudanian zone where the switching probability amounts to 20 % for an increase in the inter-annual rainfall variability.

There are also studies emphasizing a relationship between drought events and health outcomes where the moderating effect may be found in nutrition (Bauer and Mburu, 2017, Grace et al., 2012). These studies will be reviewed in the risk coping section 2.4.1.

Thus, the studies cited in the previous passage indicate that drought events have devastating effects on food security. However, it also shows that the household food security situation degrades and the effect of redistribution of food within a household is less pronounced. As it will be shown in a subsequent part, this conclusion will change when considering the effects of food price volatility on food security.

2.3 Impact of food price volatility shocks on households

As a next step of the review, studies and evidence on potential welfare effects of food price shocks will be reviewed. As in the preceding parts, the review focus will be on quantifying the effects of changing food prices with regards to different outcome variables.

The adverse effects of rising and volatile food prices received broader attention with the emergence of the global food price crisis in the years 2007-08 where global food prices reached all-time highs in several LDCs. Price increases were a phenomenon before but food price increases peaked in the years 2007-08. As the subsequent systematic review will show, the welfare effects are not as clear-cut as with respect to drought influences.

As low-income households are producer and consumer of staple foods at the same time, it will be important to judge whether the positive impacts of price increases from a producer perspective outweigh the negative effects from a price increase from a consumer perspective (Ivanic and Martin, 2008). Conventional wisdom suggests that the impact of a transitory food price shock is limited as long as households have access to assets, insurance markets and credit (cf. Alem and Söderbom, 2012). As this is not globally fulfilled, households may suffer heterogeneously from food price shocks.

2.3.1 Food price volatility induced poverty effects

In a first step, studies using poverty measures as their variable of interest will be reviewed. Poverty measures used in the reviewed studies are poverty head count ratios, poverty deficit measures or poverty threshold measures.

Dessus et al. (2008) focus on poverty effects of increasing food prices by calculating the amount of money necessary to raise incomes of affected households above the poverty line. This monetary amount is phrased as the *poverty deficit (PD)*. As the authors are concentrating on urban poor net sellers of food, income increases due to increasing food prices can be excluded from the analysis. Their sample comprises household data from 72 LDCs. Their main finding is that the PD ranges from 0.2 to 2.8 of a respective countries' *gross domestic product* (GDP). However, they emphasize that the majority of costs stems from a growing poverty deficit of those who were below the poverty line even before the price shock.

Benson et al. (2008) asses the vulnerability of Ugandan households towards changes in food prices. They find that the majority of Ugandan households can be considered as net buyers of food and are thus primarily negatively affected by food price increases. On the economy level, Uganda is able to provide most of the consumed foods internally and does not rely on international imports of staples. Thus, the country can shield its population fairly well from food price rises at international markets. However, Uganda has to import large shares of maize consumed, thus households consuming maize are facing struggles with price rises. Hence, the study concludes that in particular the maize consuming households are suffering from price increases.

Haq et al. (2008) analyze the *Household Integrated Economic Survey* from Pakistan to estimate the effect of the global 2007-08 food price crisis on poverty headcount ratios. Their main finding is that the headcount ratio raised by about 5.7 percentage points among the urban population and 9.3 percentage points among the rural population. In absolute terms, 2.3 million additional urban residents and 8 million rural residents became poor according to the headcount ratio due to the food price crisis.

Ivanic and Martin (2008) perform a similar analysis and calculate the poverty rate effect[2] and its change for a set of countries in Asia and Africa using price increase data from the 2005-07 food price increase in consumption goods prices, when consumption prices increased but did not yet reach their historic peak levels. On average, they find an increase of poverty rates by about 3 percentage points, with a substantial difference between rural and urban populations (2.5 compared to 3.6 percentage points increase). While countries like Zambia and Nicaragua saw massive increases in their poverty rates by up to 10 percentage points, extreme poverty reduced in Vietnam, which benefited on average from rice price increases. The numbers presented above are first-round effects, neglecting for instance wage rate adaptations in reaction to price increases. Similar numbers are being found for first-round effects of increasing food prices by Hoyos and Medvedev (2011) who conducted a global analysis of rising food prices during the 2005-07 food price increases. They conclude that urban households were hit harder by food price

[2] They use the population share of individuals living from less than $1 per day.

increases than rural households as urban households would not benefit from the increase in agricultural profits but would rather suffer from the loss in purchasing power as consumption goods are getting more expensive. According to their estimations, the food price increase resulted in 155 million individuals who fell below the poverty line of $1.25 per day additionally. The strongest increase took place in East Asia and Pacific countries where rural households were more strongly affected than urban households.

Using data from a second price increase in the years 2010-11, Ivanic et al. (2012) make a global assessment of poverty measures. They confirm their results from their previous study that, with the exception of Vietnam, all of the countries in their set suffered from the food price surge and experienced net increases in their poverty headcount measures. What should be noted as well is that the food price increase led to a redistribution of poverty. This is shown by Ivanic et al. (2012) who find that in principle, in all countries there exist population groups which benefited from the price increases while others lost welfare measured by the change in the poverty gap. The net effect is usually negative ranging from an increase of 0.06 % in Cote d'Ivoire to 1.28 % in Bangladesh with the exception of Vietnam where the poverty gap declined by 0.19 %.

Using a simulation study from the Philippines, Fujii (2013) finds that a hypothetical 10 % increase in all food prices would lead to an increase in the head count poverty index of 6.5 percentage points among the rural and 4.5 percentage points among the urban population. Hence, this study deviates from the conventional wisdom that rural households are on average less affected by food price increases compared to urban households. They argue that the share of very poor households is higher among the rural compared to the urban population. Hence, those very poor households induce a downward bias in the simulation.

Akter and Basher (2014) estimate the poverty effects of the 2007-08 rice price increase in Bangladesh using head count rates. Overall, the poverty head count increased from 6 % in 2007 to 21 % in 2010. Mean difference tests in poverty growth rates between affected and non-affected households were insignificant, hence indicating that food price increase impacts are heterogeneous across the groups of affected and non-affected households.

Most of the above cited studies assume that consumer and producer price levels changed proportionally. This assumption has been criticized by Dawe and Maltsoglou (2014) who argue that producer and retailer prices neither reflect a similar cost structure nor have market participants the same market power. Hence, non-proportional price changes would be evident. Under the assumption of non-proportional price changes for producers and retailers, Minot and Dewina (2015) estimate poverty effects from the 2007-08 food price crisis on urban and rural households in Ghana. They find that poverty rates increase. However, the increase is rather small as their estimates suggest an increase from 11 % to 11.2 % among urban households in the short and long term respectively. In addition, rural households will benefit in the long term from rising food prices such that poverty rates would decrease from 35 % to 34.9 % under proportional price changes. Considering non-proportional producer and retail price changes, the authors estimate poverty decreasing effects in the short and long term by up to 2.4 percentage points among the rural households while the result for the urban poverty rates remains unaffected compared to the proportional price change assumption.

Increasing food prices have substantial effects on poverty outcomes in LDCs. At the same time, they also contributed to reallocations of welfare and income within a country. However, with the exception of Vietnam, the net welfare effect of food price variability was negative.

2.3.2 Food price volatility induced food security effects

Other studies estimated the welfare effects of food price surges using measures of household-level food security. Kumar and Quisumbing (2013) estimate the effect of the 2007-08 food price crises on Ethiopian households. Their analysis takes into account gender-specific effects and also other household characteristics. By estimating a linear probability model, they ask households whether they incurred a food price shock in the two years preceding the survey. They find that being a net buyer of food increases the likelihood to report being negatively affected by a food price shock of up to 20 %, although this result may also be driven by other village specific fixed effects. In all of their specifications, female headed households are more vulnerable than male headed households to suffer from food price shocks. Compared to male headed households, female headed households exhibit a 9 % higher probability in experiencing a food price shock.

D'Souza and Jolliffe (2012) estimate the effects of the 2007-08 food price crises in Afghanistan using caloric intake and diet diversity as their variables of interest. They conclude that it is inappropriate to use caloric intake as a variable of interest to evaluate the consequences of food price shocks as low income households tend to vary quality rather than quantity. Stated differently, low income households have lower price elasticities in calorie consumption but higher quality demand elasticities than high-income households. To quantify the effect, a one percentage point increase in wheat prices decreases calorie consumption by about 6 % for the second income decile of the income distribution while it decreases caloric intake of about 38 % for the ninth decile of the income distribution. Regarding the diversity of food consumed, a one percentage point increase of wheat prices decreases the diversity of food consumed by 25 % for the lowest income decile and 19 % for the highest.

As the discussion on drought effects has shown, there exist also gender-specific effects of food price volatility. Whether there is an effect of intra-household reallocation of food –for instance differences between female and male headed households– is questionable. Kumar and Quisumbing (2013) report no significant differences between food price increase coping strategies between female and male headed households, such as cutting served meals. Furthermore, it is found that poor households are more likely to trade quantity against quality as there exist minimum requirements with respect to caloric intakes. Hence, low income households have to decrease the quality of food consumed instead of the quantity, potentially opening space for issues such as malnutrition and inadequate food intake among children.

2.3.3 Food price variability: Miscellaneous effects

Besides measures of food security or poverty effects, there are some studies focusing on consumption effects but also classical welfare measures such as the compensating variation.

Caracciolo and Santeramo (2013) estimate the welfare effects of rising food prices in Tanzania, Ethiopia and Ghana using the compensating variation. Thus, they estimate the amount of money necessary to compensate households for a price increase holding the utility level constant. Their main finding is that while in Tanzania there are winners and losers of rising food prices, the situation in Ghana and Ethiopia is more homogeneous indicating that all groups of households will lose welfare after experiencing a food price shock.

Rodriguez-Takeuchi and Imai (2013) simulate welfare effects of the 2007-08 food price surges in Columbia. Their welfare measure is constructed by calculating the compensating monetary amount which would be necessary to maintain the pre-crisis utility level. After adjusting the poverty lines, Rodriguez-Takeuchi and Imai

(2013) find that households in the lowest income quintile lost 7.9 % of their welfare while individuals in the highest income quintile lost 1.6 % of their welfare, such that the food price crisis induced higher burdens for low-income households and increased wealth inequality in Colombia.

Dimova and Gbakou (2013) analyze the effects of rice price changes on consumers in Côte d'Ivoire. Their main finding is that the food price increase led to a redistribution of income from middle income households in urban areas to poorer households in rural areas. The authors argue that rural households could react to price increases by a change in their production program while urban consumers only felt the consequences of increasing staple foods prices.

Similar findings are presented by Jacoby (2016) who simulates the welfare effects of rising food prices on rural households using household data from India. He finds that first round effects of food price increases have negative effects on net-buyers of food. Due to production adaptations in reaction to the price increase, households adopt their production portfolio such that second round welfare gains outweigh first round welfare losses. Consequently, food price increases lead to a redistribution of welfare, from net buyers to net sellers.

Macroeconomic evidence is provided by Combes et al. (2014). The authors use consumption as their variable of interest and estimate the impact of food price shocks as well as food price volatility on consumption levels and consumption growth. Using a sample from several LDCs, their main finding is that food price shocks have positive effects on countries whose vulnerability[3] for food price shocks is low, i.e. because their openness to trade or the degree of imported food is relatively low. However, if food price vulnerability is sufficiently high, food price shocks decrease the level of per capita consumption as well as it increases the variability of consumption growth.

Table 2-1 will summarize the review on rainfall and food price variability induced welfare effects on a glance.

[3] Vulnerability has been measured along several dimensions: Degree of food dependency, Food import burden, Share of food imports, Level of GDP per capita relative to other countries.

Table 2-1: Studies quantifying welfare effects of rainfall and food price variability

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Rainfall induced **expenditure** effects					
Dercon (2004)	Ethiopia	1989-1997	Drought	Consumption growth rates	10 % rain shortfall leads to a 5 % reduction of food consumption growth and to a 3 % reduction of overall consumption growth rate
Dercon et al. (2005)	Ethiopia	1999-2004	Drought	Log of per capita consumption	Experiencing a drought lowers per capita consumption by about 19 %
Skoufias and Vinha (2013)	Mexico	2002, 2005/2006	Rainfall variability	Consumption per capita	The household’s ability to protect its consumption from weather shocks depends on the climatic region and the timing of shock occurence
Skoufias et al. (2012)	Indonesia	2000	Rainfall variability	Expenditure per capita	Monsoon delay of one standard deviation reduces real per capita food expenditures by about 13 %
Porter (2012)	Ethiopia	1994-2004	Rainfall variability	Consumption per capita	Consumption dropped between 7 and 25 % for villages where actual rainfalls were in the bottom quintile of the 30-year rainfall distribution

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Arouri et al. (2015)	Vietnam	2004-2010	Flood and Drought	Consumption and expenditure per capita	Expenditures per capita decreased by around 4 % following a flood or drought event.
Hill and Porter (2017)	Ethiopia	2004/2005 and 2010/2011	Rainfall variability	Food and non-food expenditures	10 % percent drought induced crop loss results in a 3 % reduction in consumption
Rainfall risk induced **income** effects					
Molua (2011)	Cameroon	NA	Rainfall variability	Agricultural income	Marginal increase of weather variability reduced expected profits of female (male) owned farms by about 15 % (14 %)
Porter (2012)	Ethiopia	1994-2004	Rainfall variability	Agricultural income	Rainfall levels in the bottom quintile of the long-term rainfall distribution lead to a reduction in crop income of about 17 %
Thiede and Gray (2017)	Indonesia	1993-94, 1997, 2000, 2007-08	Temperature and rainfall variability	Agricultural income	Marginal deviation from the long-term temperature mean results in a 1.67 units decrease in farm profits while farm profits are insensitive towards Monsoon onset delays
Pandey et al. (2007)	China, India and Thailand	1970-2002	Climatic (Drought)	Agricultural income	Drought events reduce income by about 24-58%

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Rainfall risk induced **food security** effects					
Generoso (2015)	Mali	2005	Rainfall variability	Food security index	Increasing rainfall variability increases the likelihood of switching to lower food security classes by about 20-38 %
Hoddinott and Kinsey (2001)	Zimbabwe	1993-1997	Drought	Child growth rate	Children aged 12 to 24 months lose 1.5 $\pm$ 2 cm of growth in the aftermath of a drought
Food price volatility induced **poverty** effects					
Akter and Basher (2014)	Bangladesh	2006/7-2009/10	Food price variability	Poverty head count	Poverty head count rates increased from 6 to 21 %
Dessus et al. (2008)	20 LDC	2005	Food price variability	Poverty deficit	Poverty deficit ranges from 0.2 to 2.8 of GDP
Haq et al. (2008)	Pakistan	2004/05	Food price variability	Poverty head count	Headcount ratio raised by about 5.7 percentage points among the urban population and 9.3 percentage points among the rural population
Ivanic and Martin (2008)	9 LDCs	2005-2007	Food price variability	Poverty rate ($1/day)	Increase of poverty rates by about 3 percentage points on average, Division between several countries with increases (Nicaragua, Zambia) and reductions (Vietnam) in poverty rates

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Food price volatility induced **poverty** effects (ctd.)					
Hoyos and Medvedev (2011)	76 LDCs	2005-2007	Food price variability	Poverty rate ($1.25/day)	155 million fell below the poverty line due to food price increase while the strongest increase was observed in east Asia and the Pacific states
Ivanic et al. (2012)	28 LDCs	June – December 2010	Food price variability	Poverty headcount Poverty gap	Poverty gap increases in all countries but one (0.06 to 1.28 % increase and -0,19 % decrease in Vietnam
Fuji (2013)	Philippines	2000-2006	Food price variability	Poverty head count	A simulated 10 % increase in food prices would lead to a 6.5 (rural) and 4.5 (urban) percentage points increase in poverty head count
Minot and Dewina (2015)	Ghana	2005-2006	Food price variability	Poverty rate	Under proportional price changes, increase in poverty rates by about 0.2 percentage points for urban households. Under non-proportional price changes reduction in poverty
Food price volatility induced **food security** effects					
Kumar and Quisumbing (2013)	Ethiopia	1994-1997, 2004, 2009	Food price variability	Self-reported food security	Being a net food seller increases the likelihood of being affected by a negative food price shock by 20 %

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Food price volatility induced **food security** effects (ctd.)					
D'Souza and Jolife (2012)	Afghanistan	2007-2008	Food price variability	Caloric and diet diversity	A one percentage point price increase decreases calorie consumption by about 6 % for the second income decile and 38 % for the ninth income distribution decile
Rodriguez-Takeuchi and Imai (2013)	Colombia	2006-2007	Food price variability	Compensating variation	Households in the lowest income quintile lost 7.9 % of their welfare while individuals in the highest income quintile lost 1.6 % of their welfare

Remarks: Observation periods relate to the observation period for the household level data. The price data may stem from later periods.

2.4 Risk management and risk coping

The last sections were about to review the evidence and literature on effects of drought events and food price increases on several household-level outcome variables. While drought events were uniformly negative for all concerned households, the consequences of food price shocks are more fragmented and depend on household and economy fundamentals, geographic location as well as whether first or second round effects are taken into account. While poor net buyers and in particular poor urban households were the ones most affected by food price volatility, food producing rural households could benefit from rising food prices due to second round effects such as adopting production plans or raising additional labor related income due to rising wages. Hence, while drought events lead to a uniform reduction of welfare, changing food prices rather lead to redistribution in incomes.

The next section is particularly concerned with coping strategies of households in the context of drought and food price risks. In the literature, one finds a multitude of studies identifying several coping and adaption strategies. This review, however, will put a focus on the quantification of consumption and factor allocation responses as well as on the coping power of labor markets.

2.4.1 Consumption responses

Several authors address risk coping issues in the context of food price variability by estimating demand or consumption elasticities of staple food demand.

Wood et al. (2012) estimate substitution effects for Mexican households in the aftermath of the 2007-08 food price crisis during which Mexico suffered from a severe increase in maize prices. Surprisingly, their analysis reveals that demand elasticities for meat are much smaller than for fruits or vegetables, indicating that meat consumption substitution is rather low while fruits and vegetables are more likely to be substituted in case of price increases. This rather surprising result holds for all population subgroups under study.

Martuscelli (2016) estimates uncompensated demand and supply elasticities of food consumption using household data from Tanzania. He finds that for a one percentage point increase in staple food prices, demand for staple food decreases by about 1.14 %. His analysis also shows that the demand elasticity is more pronounced than the supply elasticity, differentiating for net-buyers and net-sellers of food.

Other scholars draw on the effect of consumption levels (Yilma et al., 2014, Alem and Söderbom, 2012) while others focus more on nutritional diversity and quality (D'Souza and Jolliffe, 2014, D'Souza and Jolliffe, 2012) or intra-household distribution of food (Kumar and Quisumbing, 2013).

Yilma et al. (2014) analyze coping strategies of Ethiopian households for different types of shocks. Experiencing an economic shock, therein included drops of output prices, increases the likelihood of reducing food consumption by about 24 %. The same probability after experiencing natural shocks – droughts, floods, storms or earthquakes – equals 40 % on average. Thus, cutting food consumption is along with dissaving the most common response to these two shock types.

D'Souza and Jolliffe (2012) estimate the impact of the 2007-08 food price crisis on food security measures in Afghanistan during which food prices doubled. Food security measures comprise the real value of per capita food consumption but also measures of nutritional diversity. Their main finding is that a one percent increase in wheat prices leads to a reduction in real per capita consumption by about 0.2 %. Moreover, the authors find that households reduce their caloric intake from expensive to relatively cheaper calories, hence shifting consumption away from meat and vegetables towards grains.

Kumar and Quisumbing (2013) analyze gender specific responses to food price shocks for Ethiopian households. The main result is that households cut back quality as well as quantity of consumed food in reaction to food price shocks. However, the cut back in quality is more pronounced than the cutback in quantity, reflecting basic quantity requirements rather than quality requirements. In addition, consumption cutbacks mainly occur with adults in the households, consumption cutbacks among children are smaller and equally distributed between genders.

Alem and Söderbom (2012) estimate the effect of the 2008 food price surge on urban Ethiopian households and assess whether households are differently vulnerable towards changes in food prices, measured by their consumption reaction. According to the authors, urban Ethiopian households produce little food on their own but spent a high proportion of their income on food consumption. The authors asked respondents whether they cut back their consumption as a reaction towards food price shocks. Most likely to reporting consumption cutbacks are casual worker whose income is rather unsteady. In addition, assets are the main driver of preventing households to cutting back food consumption.

Avalos (2016) is concerned with longer lasting consumption pattern changes of increasing food prices between 2002 and 2012 differentiating between rural and urban Mexican households. According to the authors, general food prices rose by about 134 % in the mentioned period. The authors estimate budget shares for eight different expenditure categories and predict from these estimations the budget share that should show up if Engel's Law would hold. For all categories of households –poor urban and poor rural households- observed budget shares for food consumption exceed the predicted ones while budget shares for non-necessity goods decreased. This shows that households under study significantly changed their consumption patterns in reaction to food price increases. Households had to shift more funds towards food consumption and they did so by reducing expenditures on health care and education.

Other authors draw on the potential effect of food price volatility and drought shocks on child nutrition outcomes as these events lead to a consumption response and hence to changes in the nutritional status of children (Arndt et al., 2016). Arndt et al. (2016) analyze the impact of increased volatility levels in the aftermath of the 2007-08 food price crisis on child nutrition outcomes and compare them with periods where food price inflation was lower using data from Mozambique. Their main result is that measures of child malnutrition were lower during periods of comparably lower food price inflation. In addition, they find that rural populations are more severely affected by food price inflation compared to urban regions. This may be due to the production structure or different chances to raise additional income.

Generally, it is found that food price changes lead to significant changes in consumption patterns by affected households. Not only do households cut back the quantity of food consumed, they do it also by substituting low-quality against high-quality food. This practice raises concerns about long-lasting nutritional deficiencies, in particular among children.

The evidence of consumption responses with respect to drought events is rather scarce and centers around the question whether consumption streams are smoothed by selling assets during times of hardship (cf. Carter and Lybbert, 2012, Kazianga and Udry, 2006, Hoddinott, 2006). However, there is some recent evidence that drought events may impacting on child health outcomes, providing evidence that drought events lead to consumption cuts and deteriorating child nutrition (Bauer and Mburu, 2017, Grace et al., 2012). Opiyo et al. (2015) report food consumption cuts as a standard risk coping instrument among Kenyan pastoralists, applied by almost 60 % of the respondents.

2.4.2 Labor time reallocation

This section is aimed to review the evidence of risk potentially impacting on factor reallocation within the household in reaction to shocks. Particular attention is given to labor reallocation decisions made by households.

Rose (2001) analyses labor time allocation decisions in reaction to drought events in rural India. She estimates the likelihood of labor market participation of agricultural households and finds that rainfall shocks *(ex post)* as well as rainfall risk *(ex ante)* increase it. Thus, labor time allocation is used to spread the agricultural production risk *ex ante* and to cope with rainfall shocks. In contrast to these results, Kanwar (1999) finds that labor market participation may also be negatively affected by rainfall variability. He explains this finding by deteriorating labor market conditions following negative rainfall shocks.

The results of Rose (2001) are confirmed by the study of Cameron and Worswick (2003) who find evidence that labor supply increases in reaction to shock experiences. Using data from the *IFLS*, the authors test whether households smooth income streams using labor time allocation by splitting up their labor time potential between farm work and supplying labor. They find evidence that after experiencing a crop loss on the family farm, household members tend to reallocate labor rather than increasing the overall time spend working on the own farm. In particular male family members tend to reallocate their labor time potential towards more productive activities than farming in reaction to crop loss.

This result is supported by Kenjiro (2005) who pursues the question whether households are able to cope with systemic shocks better than with idiosyncratic shocks. Using data from rural Cambodia, the author finds that in reaction to a crop loss shock, earning additional income by increasing or reallocating labor time was an often applied yet effective strategy to raise further income *ex post.* Surprisingly, the author finds that households had fewer problems to cope with crop loss than with illness as medical expenditures require large payments and are indivisible.

A different approach has been chosen by Menon (2009) and Skoufias et al. (2017) who draw on the occupational diversification by estimating the probability that a household head and its dependents have the same occupation using shock variables as covariates. Menon (2009) uses data from Nepal and finds that rainfall uncertainty and the probability that non-head members have a differing occupation from the household-head is positively related. Thus, there exists evidence that household specialization is sensitive towards rainfall variability and that the degree of intra-household specialization is lower where rainfall variability is higher. Similar results are being found by Skoufias et al. (2017) for India, showing that rainfall variability and rainfall outcomes influence the probability of equal occupations in a negative way indicating that rainfall variability lead to a diversification of income structures.

Corral and Radchenko (2017) are using a model of spatial correlation between households to determine the influence factors of income source diversification. While they confirm spatial dependence in occupation choice patterns, rainfall variability is another major driver of income source diversification. Thus, more variable rainfall levels lead with a higher probability to a more diversified income portfolio.

A different argument is being made by Carter et al. (2007). The study analyzes the post-drought asset recovery in Ethiopia. Among other factors, labor market access increases the capital accumulation growth rate and is thus important for asset protection and recovery in post-disaster periods.

To summarize, labor markets are an important instrument to cope with adverse weather events. They allow households to diversify their income portfolio *ex ante* and to raise additional income in the post-drought period.

2.4.3 Child labor and school enrolment

The previous section looked at factor reallocation as a reaction towards risk such as drought induced production risks. However, there are other forms to cope with shocks by raising additional income using labor markets. In the following section, studies on raising additional income from the production potential of children will be reviewed. This coping strategy has two possible effects on household income: On the one hand, there might be a direct income effect as children are used to increase the labor time potential and thus to expand the labor time available to the household. This increase in labor time potential can then be used to increase on farm labor input or the supply of labor. On the other hand, reallocating children from school into the labor time potential releases funds as schooling is linked to direct costs such as schooling fees, transportation or the costs of school uniforms (cf. Janvry et al., 2006). Of course, using children's work force and withdrawing them from school induces negative effects with respect to human capital formation. This opens the discussion of whether microinsurance has the potential to decrease the incentive to make use of the child labor force (Landmann and Frölich, 2015).

Janvry et al. (2006) analyze school enrolment decisions and child labor dynamics of Mexican households in the aftermath of droughts and natural catastrophes such as hurricanes, floods or plagues. They find that the occurrence of natural catastrophes decreases school enrolment by 3.2 percentage points while school enrolment stays unaffected from drought events. The authors explain this observation by arguing that drought events are relatively frequent in Mexico. Thus, households adapted to these events *ex ante* and hence need not to react by a decrease in school enrolment. By the same token, drought events do not significantly affect child labor decisions but rather decrease the burden of child work. This is explained by deteriorating labor market conditions in drought phases and an excess supply of adult labor. When wages decrease in a surrounding of excess labor, opportunity costs of schooling also tend to decrease.

Other scholars support the finding that child labor is used as a risk coping strategy such as Beegle et al. (2006), analyzing household data from Tanzania. Following a crop loss, child labor increases in various fixed effects estimated specifications. Child labor is particularly distributed towards domestic work or collecting fire wood while the time allocated to farming increases in an unsystematic way.

Gubert and Robilliard (2007) estimate a model of school entrance and drop out probabilities using household data from Madagascar. While school entrance probabilities are unsystematically affected by rainfall induced income shocks, dropout rates are higher when income shocks are negative. The study does not analyze where the child labor force is used after dropping out of school.

Focusing on school enrolment in several African and south-east Asian countries, Alvi and Dendir (2011) find no evidence of drought events impacting on school enrolment. They explain their finding by the equalization of the income and substitution effect between falling wages in drought conditions and the lack of missing child labor income. These two effects cancel out and, according to the authors, are able to explain the observed pattern.

Zamand and Hyder (2016) analyze the potential effect of droughts and floods on school enrolment outcomes in Ethiopia, India, Peru and Vietnam. They test the hypothesis that income loss is substituted by child labor and a decreased school enrolment rate in the aftermath of a weather induced event. However, their results are rather inconclusive across the countries under study. In none of the mentioned study regions, school enrolment is affected by the occurrence of floods or droughts. However, performance measures of students are negatively affected by drought and flood occurrences, indicating that students invest less time into learning as their labor force might be needed to cope with the shock event. This result holds across all countries under study.

Shah and Steinberg (2017) concentrate on the relation between drought events and human capital formation in rural India. While current and previous year rainfall shocks affect measures of acquired human capital, such as math scores and reading abilities negatively, school enrolment is only negatively affected by the lagged rainfall shock variable. Hence, school dropout rates react to drought events with a lag of one year while rainfall shocks of the same year do not exert a systematic influence on school dropout rates. However, the deteriorating results in math and reading skills imply that drought events lead to a decrease in human capital accumulation effort and are thus an indication for intra-household reallocation of labor resources.

Evidence on the relation between intensity and extent of child labor as a coping reaction with respect to food prices is rather scarce. Recent contributions to the discussion stem from Frempong and Stadelmann (2017) and Hou et al. (2016).

Frempong and Stadelmann (2017) find significantly positive effects of food price shocks on the decision to work as well as on the extent of working for Ugandan households. Thus, the study provides evidence that child labor is used to cope with the adverse consequences of food price shocks.

By presenting evidence from Pakistan from the period 2008-10, Hou et al. (2016) report that the probability of school enrolment decreases with the occurrence of self-reported food price shocks while the likelihood of child work increases in the poorest income quantile of the income distribution. More objective results are being obtained by regressing school enrolment and work decisions on changes of wheat prices where the enrolment and child labor pattern persists: While school enrolment decreases, the quantity of child labor increases in the poorest income quantile only. In addition the analysis shows that girls and rural households are more strongly reacting towards changes in food prices in altering their school enrolment and working decision.

2.4.4 Wage reactions

The previous section reviewed strategies that are aimed to smooth consumption in reaction to food price and rainfall shocks. Labor has been found to be an important instrument as labor markets could be used to increase child labor, to reallocate labor to sectors that are less affected by rainfall shocks or to diversify income portfolios prior to realized income shocks.

Another important question which arises in the context of risk coping through labor markets is whether wages react to shock events and thus provide implicit insurance by adapting wages. For instance, higher food prices could lead to higher production incentives and thus to a higher demand for agricultural labor, resulting in rising agricultural wages (cf. Lasco et al., 2008). In this sense, agricultural workers would receive a food price shock compensation from their employer and thus dispose of an informal insurance instrument.

Jayachandran (2006) develops the argument that productivity shock induced wage cuts are greater where labor supply is more inelastic. Inelastic labor supply in his analysis is due to lacking opportunities to migrate or to tap financial markets by borrowing or depleting savings. Hence, labor markets in regions where the population is unlikely to migrate or where financial market access is limited will experience a higher variability in agricultural wages after experiencing production shocks. Whether labor markets and wages act as implicit insurance depends on the elasticity of demand and supply of labor, while elasticities are determined by exogenous fundamentals.

Lasco et al. (2008) look into short- and long-run wage elasticities as a reaction towards rice price changes in the Philippines. Their main finding is that there is a positive relation between agricultural wages and rice prices, estimating short-run wage elasticities between 0.29 and 0.43 and 0.7 and 1 in the long-run. However, even under the most optimistic simulation, rice price increases are compensated after two years at the earliest.

In a recent assessment, Jacoby (2016) studies wage responses in reaction to price changes in rural India. His main finding is that price changes do not perfectly translate into changing wages, neither for manual nor for non-agricultural labor such that it can be concluded that wage responses are rather an imperfect implicit insurance for changing food prices. Kaur (2017) finds that nominal wages display nominal downward rigidity. Hence, wages increase in the case of a positive production shock but they do not adapt downwards if a negative production shock occurs. On the one hand, this increases the ability of labor markets to smooth income for those who have employment. On the other hand, this could also have a negative impact on the chances to enter labor markets for those who seek to smooth their income profile in the aftermath of a negative rainfall shock and thus are willing to enter the labor market.

This is also the synthesis of the preceding paragraph. Wages do react with respect to price changes, but they will do it with a lag of several years and in smaller magnitude. Thus, net food consumers perceiving wage income will likely see their welfare to decrease when food prices increase.

With respect to rainfall induced production shocks, the evidence on factor reallocation has shown that labor markets are an often used yet imperfect instrument to cope with rainfall shocks as labor market opportunities may deteriorate in the aftermath of a shock event (Kanwar, 1999).

Table 2-2 will summarize the main insights on the risk coping and management section on a glance.

2.5 Conclusions

The present chapter reviewed recently published empirical literature on the quantification of welfare effects induced by rainfall and food price shocks in developing and emerging countries. The review systematized the relevant literature according to the underlying dependent variables. Variables of interest were changes in expenditure patterns, income effects, poverty measures such as headcount ratios or poverty thresholds but also effects on the food security situation of concerned households. The main insight from the drought shock analysis was that they affect households in a relatively homogeneous way. In contrast to food price shocks, households always loose welfare from drought shock events. However, the magnitude of welfare losses may change in dependence of household or geographical fundamentals. In contrast, food price shocks lead to a redistribution of welfare rather than to a decrease of it as particularly net food selling households benefit from food price increases. On the losing side of increasing food prices, most studies found poor urban households which have only limited opportunities to adopt production plans or to trade quality for quantity of consumed food. Overall and for most economies, however, the welfare decreasing effects outweigh potential welfare gains.

The second part of the review was concerned with informal risk management strategies of affected households. The analysis focused on labor related strategies such as to increase the labor time potential using child labor, to reallocate labor between different income generating activities or to use wage reactions as a form of implicit insurance. It has been shown that labor is an adaptation strategy widely used for risk coping.

Table 2-2: Studies on shock response quantification

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Consumption responses					
Wood et al. (2012)	Mexico	2006	Food price shocks	Demand elasticities	Substitution elasticity for meat is lower than for vegetables and fruits, households substitute meat for fruit
Martuscelli (2016)	Tanzania	1991-1994, 2004	Food price shocks	Demand elasticities	A one percentage point increase in staple food prices decreases demand for staple food by 1.14 %
Yilma et al. (2014)	Ethiopia	2011	Price shocks	Food consumption	Experiencing a drop of output prices increases the likelihood of reducing food consumption by about 24 %.
D'Souza and Joliffe (2012)	Afghanistan	2007-2008	Food price shocks	Consumption per capita	A one percent increase in wheat prices leads to a reduction in real per capita consumption by about 0.2 %
Kumar and Quisumbing (2013)	Ethiopia	1994-1997, 2004, 2009	Food price shocks	Consumption per capita	Households cut back quality as well as quantity of consumed food, while cut back in quality is more pronounced than the cutback in quantity
Avalos (2016)	Mexico	2002-2012	Food price shocks	Consumption budget shares	Households had to shift more funds towards food consumption and they did so by reducing expenditures on health care and education which changed established budget shares of consumption.

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Consumption responses (ctd.)					
Arndt et al. (2016)	Mozambique	2008-2009	Food price variability	Measures of child malnutrition	Measures of child malnutrition were lower during periods of comparably lower food price inflation and more pronounced in rural than urban regions.
Opiyo et al. (2015)	Kenya	NA	Drought	Food consumption	Almost 60 % of the respondents cut their food consumption levels in reaction to drought events.
Labor time reallocation					
Rose (2001)	India	1968-1971	Rainfall variability	Labor market participation	Likelihood of labor market participation increases in the rainfall shocks *(ex post)* as well as in rainfall riskiness *(ex ante)*.
Cameron and Worswick (2003)	Indonesia	1993	Rainfall variability	Consumption variability	Male family members tend to reallocate their labor time potential towards more productive activities than farming after a shock event.
Kenjiro (2005)	Cambodia	2002	Crop loss	Consumption variability	In reaction to a crop loss shock, earning additional income by increasing or reallocating labor time was observed *ex post*
Menon (2009)	Nepal	1995-1996	Rainfall variability	Occupational diversification	Household specialization is sensitive towards rainfall variability and the degree of specialization is lower where rainfall variability is higher
Skoufias et al. (2017)	India	2002-2003	Rainfall variability	Occupational diversification	Rainfall variability and realized volatility lead to a diversification in income structures.

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Corall and Radchenko (2017)	Nigeria	2010-2011	Rainfall variability	Occupational diversification	Spatial dependence in occupation choice patterns and rainfall variability are the major drivers of income source diversification
Child labor and school enrolment					
Janvry et al. (2006)	Mexico	1997-2000	Droughts, NatCat	School enrolment	The occurrence of natural catastrophes decreases school enrolment by 3.2 percentage points while school enrolment stays unaffected from drought events
Beegle et al. (2006)	Tanzania	1991-1994	Crop loss	Extent of child labor	Following a crop loss, child labor is distributed towards domestic work while the time allocated to farming increases in an unsystematic way
Gubert and Robilliard (2007)	Madagascar	1995-2002	Rainfall variability	School enrolment	While school entrance probabilities are unsystematically affected by rainfall variability, dropout rates are higher when income shocks are negative and positive if the income increases.
Alvi and Dendir (2011)	African and Asian LDCs	1998-1999	Rainfall variability	School enrolment	No evidence of drought events impacting on school enrolment.
Zamand and Hyder (2016)	Ethiopia, India, Peru, Vietnam	2009	Rainfall variability	School enrolment and performance	No systematic impact of rainfall variability on school enrolment but school performance measures

Study	Study area	Observation period	Type of shock(s) under consideration	Dependent variable	Main results
Child labor and school enrolment (ctd.)					
Shah and Steinberg (2017)	India	2005-2009	Rainfall variability	School enrolment and performance	School enrolment rate reacts with a time lag on drought events while performance measures are immediately negatively affected
Frempong and Stadelmann (2017)	Uganda	2009-2010	Food price shock	School enrolment	Negative effect on the school enrolment rate and positive effects on the decision to work after experiencing a shock event

Remarks: Observation periods relate to the observation period for the household level data. The price data may stem from later periods.

Child labor time, for instance, is used to replace the domestic workforce of women who then work on the farm or supply labor to labor markets. While school enrolment was largely unaffected by shock events, school dropout rates as well as measures of human capital formation effort deteriorated.

With respect to labor time reallocation, the evidence was mixed with studies identifying worsened labor market conditions in the aftermath of a drought event and others identifying an increase in labor supply in reaction to shock events. Most likely, labor reallocation decisions will depend on the characteristics of labor markets: A rainfall shock will lead to worsening agricultural labor market conditions while non-agricultural labor markets may remain unaffected.

The review has also shown that wage adaptations to food price and productivity shocks do not provide perfect implicit insurance as asymmetric bargaining powers as well as long adaptation periods provide an unreliable protection.

The review has shown that households in developing and emerging countries are highly threatened by rainfall and food price risks. The review of quantifying studies has revealed significant income risks induced by rainfall failures and food price shocks. The analysis of coping strategies has shown that the realization of risks leads to suboptimal allocations of labor time, has spillover effects with respect to human capital formation or may also induce other long-lasting consequences such as impaired child nutrition and health.

These insights open the discussion towards better risk management in developing countries. It reveals new perspectives on vulnerable population groups- rural poor with respect to rainfall failure and urban poor with respect to food price increases. It also encourages labor market reforms to improve the bargaining position of laborers. Furthermore, it also links the discussion with issues of financial inclusion, to give poor households access to formal risk management instruments to better manage their production and consumption risks using microinsurance, savings accounts and credit.

3 Labor time allocation of farm households: The case of food price and rainfall variability[4]

Abstract

Subsistence farmers in low income countries are confronted with multiple risks. In reaction to them, farm households have developed several strategies to cope with yield risks to self-insure against these income shocks. Recent developments in global food markets have increased food price volatility, which, in particular, puts low-income households at risk. When small-scale farmers allocate their labor time over different income generating activities, they face the risk of uncertain purchasing power of income in the presence of food price variability. The paper analyzes the labor time allocation decision between self-employment and wage labor, taking into account the uncertain purchasing power of wages resulting from food price volatility. Using a panel structured household data set containing consumer-producer households in rural India, the labor time allocation decision between farming and labor market participation will be analyzed. The analysis reveals counterintuitive time allocation effects of risk.

[4] I gratefully acknowledge financial support from the Deutscher Verein für Versicherungswissenschaft (DVfVW e.V.). In addition, this work would not have been possible without the countless remarks and propositions from the participants of the 56th annual conference of the Indian Society of Labor Economics, the 3rd World Risk and Insurance Economics Congress, the annual conference of the DVfVW and several doctoral seminars at the Institute of Health Care & Public Management, University of Hohenheim. I particularly thank ICRISAT for providing the analyzed data.

3.1 Introduction

Life in LDCs is marked by a risky environment: Weather-induced hazards, such as uncertain rainfall or floods, diseases or other family tragedies such as illness or death of the breadwinner, as well as risks on the macroeconomic level, such as political unrest, riots and friction in international commodity markets put income streams at risk. As formal insurance and credit markets are incomplete in developing countries, informal risk management strategies have gained particular importance in mitigating income risks of farm households (Townsend, 1994). Within the set of informal risk management strategies applied by low-income farm households, labor markets are of vital importance to flattening the income fluctuations. Farm households split up their labor time potential and allocate it over different income generating activities, such as self-employed farming but also contractual labor in farming or non-farming activities. Thereby, farm households diversify their income portfolio and earn profits from selling the agricultural yield but earn wage income as well. Thus, they reduce the degree of dependency from events that determine agricultural productivity (Fernández et al., 2014, Cameron and Worswick, 2003, Rose, 2001, Kochar, 1999, Kanwar, 1999).

However, in the face of volatile and unpredictable consumption goods price changes, the diversification effect of labor time allocation may be overestimated. If consumption goods prices rise unexpectedly, this devalues wages in terms of their purchasing power. Hence, volatile food prices might put households in a situation where they are unable to purchase the amount of food necessary to substitute the amount of energy expended on the income-generating remunerated activity (Dalgaard and Strulik, 2011). Thus, by shifting time to the labor market, households diversify their production risk but have to accept the purchasing power risk of their wages induced by volatile food prices such that the magnitude of income diversification may be lower than expected.

Several studies consider the issue of farm household's labor time allocation and income diversification. First generation models find that they allocate labor time such that, in equilibrium, marginal value products of different income generating activities are equalized (Sumner, 1982, Rosenzweig, 1980). However, these first generation models leave risk considerations aside.

Other studies incorporate risk into the labor time allocation decision (Skoufias et al., 2017, Bandyopadhyay and Skoufias, 2015, Démurger et al., 2010, Menon, 2009, Taylor and Adelman, 2003, Abdulai and Crole Rees, 2001, Rose, 2001, Kanwar, 1999, Mishra and Goodwin, 1998, Mishra and Goodwin, 1997). These authors find that labor time allocation is used as a risk-coping (*ex post*) and risk management (*ex ante*) strategy to smooth income streams. Most of the studies model a rainfall or price induced yield risk as a farm activity risk while others integrate dual income risks by analyzing the labor time allocation under joint farm income and labor market income uncertainty, for instance due to unemployment risks.

None of these studies, however, takes into account the issue of consumption risk induced by food price volatility as a source of labor market income uncertainty and its effect on labor time allocation. This gap will be closed by this study. In particular, the study presented in this paper tries to answer the following questions: What is the effect of yield risks on on- and off-farm labor supply? What is the effect of food price variability induced consumption risk on on- and off-farm labor supply?

The remainder of the paper is organized as follows: Section 3.2 presents a literature review and develops the framework which is used for analyzing consumption risks. Section 3.3 describes the analyzed data and the development of the empirical model. Section 3.4 explains the results while section 3.5 concludes.

3.2 Theoretical background

3.2.1 Consumption risk

Farm households, confronted with a multitude of income risks, have developed *ex ante* as well as *ex post* strategies to cope with income uncertainty. Among others, labor time allocation is one of the strategies employed by the households under study. Thus, farm households split their labor time potential into several parts to use it for different income generating activities, mostly farming and supplying labor to the labor market.

Receiving wage income, however, means taking a consumption risk if consumption goods prices are volatile and wages are not indexed or do not adapt immediately. In this sense, unexpected price changes represent a depreciation or appreciation of wages such that the amount of consumption goods available need not be equal to the amount the household had expected to purchase when entering into the labor relationship. As the majority of expenditures are being made on food consumption, low-income households engaged in labor market relations are particularly vulnerable to changes in prices of staple food which they consume but do not produce themselves.

On a global scale, food price volatility was an issue even before the crisis in 2007-08. The discussion of the reasons for an increase in global commodity prices is still ongoing, yet their consequences are felt by low-income households in particular. Figure 3-1 below shows the evolution of the average nominal food price index since 1996 deflated by the consumer price index for three groups of countries with 2005 as the base year: those with a GDP per capita below 2.000 $ p.a. (blue), those with a GDP per capita between 2.000 and 10.000 $ p.a. (red) and those with a GDP per capita above 10.000 $ (green).

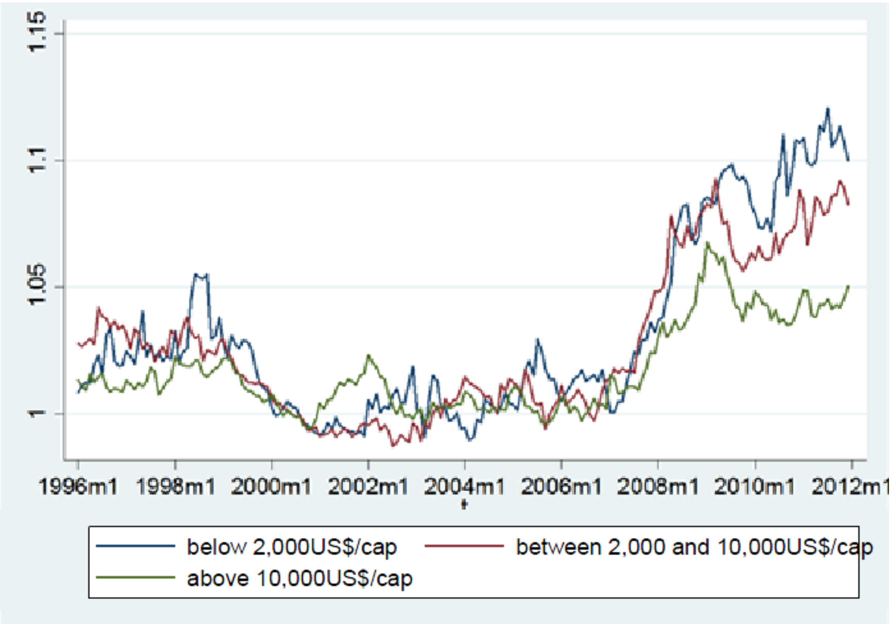

Figure 3-1: Evolution of global food prices[5]

Figure 3-1 depicts two things. First, it can be seen that the average food price index increased substantially during the food price crisis of 2007-08 in all three country groups, while the increase was stronger the poorer a country was. Thus, the poorest countries are the ones most affected by increases of average food price levels. A second fact is that the volatility of food prices is the highest in the poorest group of countries. However, while the food price crisis of 2007-08 changed the level of food prices substantially, the level of food price volatility did not increase to the same extent. The situation for the poorest group of countries is tightened by the fact that food expenditures represent the most important household expenditures in least

[5] Source: Kalkuhl et al. (2013)

developed countries (Banerjee and Duflo, 2012). Food price variability and increasing food prices became a global issue and several governments got under pressure when distressed populations revolted against rising food prices.

Figure 3-2 below illustrates the consumption risk discussion from the perspective of a consumer-producer household. The graph defines the action space of a cash crop producer, i.e. a farmer who does not seek food self-sufficiency from his own production but rather to produce crops to sell them at goods markets. This corresponds with the predominant production structure of farm households used in this study.

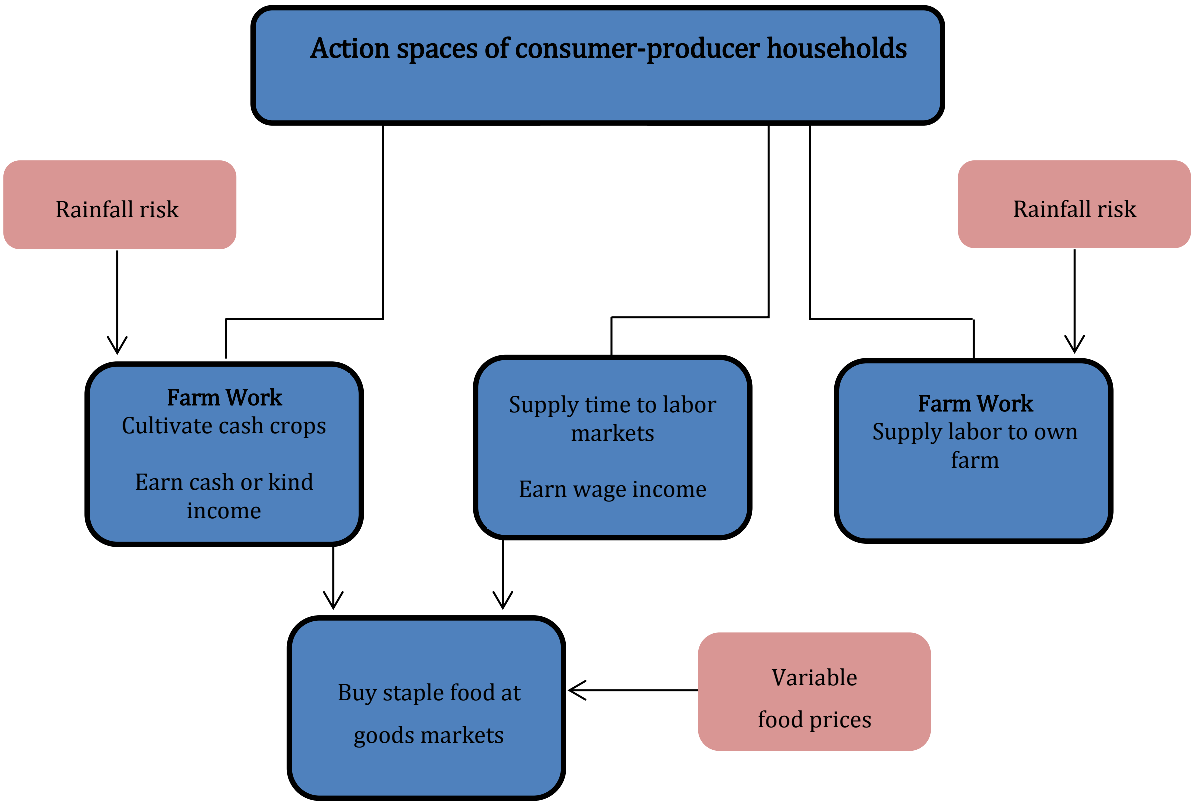

Figure 3-2: Action spaces of consumer-producer households

Figure 3-2 illustrates the action space within an informal risk management framework. A farmer on the left hand side of the graph is concentrating its labor resources in farming while the one on the right hand side splits up its labor time potential between farming and supplying time to the labor market.

If a farmer decides to specialize in farming and to plant cash crops, he faces a rainfall induced yield risk as does the producer who splits up his labor time potential. Using the income from selling the crops to agricultural markets, the specialized farmer faces a consumption risk as the income from selling his output may be devaluated by rising food prices. As the analysis aims for variable food prices, potential variability in output prices for the cash crops are unconsidered in this framework.

The same is true for the farmer who splits up his labor time potential. Receiving a wage income –cash or kind– he faces uncertainty over the amount of food he is able to purchase with his non-indexed wage income. Hence, the sources of income risks between specialized and non-specialized farmers are relatively equal. However, the specialized farmer faces a sequential income risk while the time allocating farmer faces a simultaneous income risk.

To conclude, the fact that low-income households allocate labor time towards wage-based activities creates consumption risks in the presence of food price volatility. If one considers consumer-producer cash crop producers, it turned out that the sources of income risks do not differ. However, labor time allocation changes the time structure of income risks. At the same time, labor time allocation leads to a loss in specialization but diversifies the income risk. However, the diversification effect may be overstated due to consumption risk such that the overall income risk decreases less than it had been expected by the diversifying farmer. Whether these consumption risks are affecting the decision to allocate labor time will be part of the empirical analysis in subsequent parts.

3.2.2 Literature review

In the previous section a rationale for labor time allocation decisions dependent on food price volatility was given. In what follows, labor time allocation patterns of the households under study will be analyzed more closely and a literature review on the effects of uncertainty in labor time allocation will be provided.

The aspect of time allocation between self-employed land cultivation and labor market activity has received certain attention in the scientific literature: Fundamental work in the field of farm-time allocation in a riskless framework has been made by Sumner (1982) and Rosenzweig (1980). According to these authors, time allocation depends on the value of time spent on and off the farm, determined by profits from selling the output and constant unit of time wages. As the activity rewards –profits and wages– are known with certainty, every individual is able to determine and implement its optimal time allocation according to the observable and personal fundamentals.

Subsequently, several authors conducted research on the allocation of labor time if farm-income or off-farm income is uncertain for reasons of farm-product price variability (Mishra and Goodwin, 1997), uncertain rainfall (Skoufias et al., 2017, Bandyopadhyay and Skoufias, 2015) or uncertain labor market conditions and unemployment risks (Kanwar, 1999, Mishra and Goodwin, 1998). Both sources of income risk, producer price variability and unemployment, have a significant impact on labor supply: Higher producer price variability increases the amount of time allocated to labor market activity, whereas a higher unemployment rate decreases the amount of time allocated to the labor market. The latter authors conducted their studies on the behavior of US-farmers, thus providing findings for well developed markets and industrialized countries.

Mishra and Holthausen (2002) introduced on-farm and off-farm income variability on an aggregate level into the analysis. By analyzing a sample of US-farm households from Kansas and North Carolina, they introduced farm income as well as wage variability as explanatory variables. Their main result is that an increase in farm variability stimulates off-farm employment whereas an increase in wage variability decreases the allocation towards off-farm employment.

Rose (2001) extended the analysis of farm household decision making on farm households in developing countries, in this case Indian farmers and their labor market participation in the face of lacking rainfall and induced drought risks. The author finds an increase in the *ex ante* likelihood of labor market participation for drought risks such that households anticipate drought risks. At the same time, she finds an *ex post* reaction with an increase in labor market participation probability as a risk-coping strategy. However, she only considered a single source of income uncertainty, namely, weather-related yield risks. In her formulation, offering labor is a risk management strategy to respond to weather fluctuations while labor productivity is not subject to risk.

Ruben and van den Berg (2001) find evidence that agricultural households split their time endowment between work in the cooperative and work in their own field. However, the case of time allocation between self-employment and work in a cooperative is not comparable to the case where individuals divide their labor time between self- and wage employment as long as the members of the cooperative produce food crops. Food price volatility puts those at risk who are net buyers of food and, in addition, are dependent on the purchasing power of labor market income. Members of cooperatives face some sort of natural hedge against risks that have to be borne by smallholder farm households being active in the labor market.

Other scholars are drawing on intra-household allocation of labor resources and estimate the probability that a household head and its dependents have the same occupation. Skoufias et al. (2017) and Menon (2009) find a negative effect of the riskiness of rainfall distributions on the likelihood that all household member have the same occupation. In other words, rainfall risks increase the probability that income generating activities across household members are diversified.

Kochar (1999) finds that agricultural labor markets are used as a coping instrument to absorb income shocks. However, the author’s analysis is restricted to idiosyncratic shocks, whereas food price shocks have a systemic character.

A point that has been neglected in the allocation of labor time is the issue of volatile and uncertain food prices in developing countries as an important source of labor market-related income risk. Previous studies, such as Mishra and Goodwin (1998), hypothesize that labor market related income is threatened by unemployment. However, due to growing urbanization and migration of the younger generation, unemployment is not the major issue in Indian agricultural labor markets but rather a lack of labor (Ramana Reddy et al., 2011). To the best of my knowledge, the joint uncertainty structure of rainfall and food price risks and its effect on labor time allocation in developing countries has not been considered in the literature so far. Hence, this study will complement research at this point.

3.3 Data description & Empirical strategy

3.3.1 Data

The previous section outlined the rationale that food price volatility might be a determinant of labor time allocation. In what follows, the description of the analyzed data as well as the empirical specification will be presented.

The data analyzed in this study is taken from a panel data set collected by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), which continuously surveys households in several states of India with respect to –among others– cropping patterns, input purchases, sold outputs and consumption expenditures. Due to low levels of mechanization and technology use, agricultural activity in these states is highly dependent on the intensity and correct timing of the monsoon. Hence, agricultural income is periled whenever rainfall fails.

In this study, the waves of 2009 through 2012 are used, which comprise 8,570 observation points. The study analyzes labor time allocation on the individual level. Eighteen villages in the states of Andhra Pradesh, Karnataka, Gujarat, Maharashtra and Madhya Pradesh have been chosen, as they are located in remote areas such that the households under consideration have only limited opportunities to consume from different markets in the case of adverse price shocks. Producers in the data set are primarily cash crop producers, i.e. they cultivate crops which are not produced for their own consumption but rather to be sold on agricultural markets. A small quantity of farmers produces insignificant quantities of rice and wheat, the two types of staple food which will be considered as consumption goods in the subsequent analysis. Thus, the representative consumer-producer household is a net purchaser of food even if he may produce quantities of goods intended for its own consumption.

Labor markets in these states are marked by a high degree of informality and spontaneity. In most cases, employers hire workers the day before they are supposed to start working or even in the morning of the working day. These tasks are mostly performed by day laborers who are remunerated on a piece basis, i.e. wages per units of output. While caste affiliation has only a minor influence on hiring decisions, most tasks on daily wage basis are highly gender specific (Walker and Ryan, 1990). Reported involuntary unemployment of households under study is rather low: On average, individuals were unable to find employment on 9.3 days of the calendar year for the population in the employable age between 15 and 65.

Households are primarily net food consumers; the major production good is sugarcane. Table 3-1 shows the sample's summary statistics, separated for different subgroups. Column A reflects the full sample properties of all 8,570 observation points. Column B and C further distinguish households that did not participate in labor markets (Column B) or supplied positive amounts of time towards labor market activities (Column C) but excludes inactive or individuals solely occupied with unpaid housework. Column D depicts the results of a two-sided t-test for mean differences between the subgroups in column B and C. All variables described below were measured on a yearly basis such that there is no difference between the cropping and planting season. The time allocation decision is considered to be constant throughout the whole agricultural year.

It can be seen that the educational level is on average rather low and amounts to 5.8 years of schooling in the whole sample. Non-labor supplying households show a slightly higher educational level compared to labor market participants, the mean difference is significant on any significance level.

	(A) Full sample	(B) Non labor market participating households	(C) Labor market participating households	(D) t-test for mean differences
age	35.99	34.46	37.26	***
[Age in years]	(18.01)	(21.45)	(14.22)	
yrs_edu	5.82	6.05	5.66	***
[Years of schooling]	(4.703)	(4.484)	(4.831)	
hh_size	5.73	6.00	5.34	***
[Household size]	(2.680)	(2.937)	(2.358)	
farm_size	6.66	8.06	5.31	***
[Acre]	(7.727)	(8.349)	(6.316)	
irriare	0.49	0.55	0.45	***
[% share of irrigeable farm size]	(0.412)	(0.398)	(0.422)	
degab	0.80	0.65	0.93	***
[Share with highest physical ability]	(0.402)	(0.477)	(0.255)	
male	0.52	0.44	0.61	***
[1 if male]	(0.500)	(0.496)	(0.489)	
married	0.65	0.53	0.75	***
[1 if married]	(0.477)	(0.499)	(0.432)	
revenue	500,000	610,000	340,000	***
[Revenue from farming, INR]	(1,342,209.4)	(1,561,596.3)	(1,054,769.0)	
cap_inp	26,050.47	30,465.05	20,248.96	***
[Value of physical capital input, INR]	(45,267.5)	(49,104.5)	(34,458.6)	
inc	470,000	560,000	330,000	***
[Household income, INR]	(1,308,538.5)	(1,527,897.4)	(1,029,637.3)	
farm_days	87.22	83.34	79.43	*
[Farm days per year]	(91.32)	(103.0)	(78.06)	
rain_loss	0.23	0.19	0.26	***
[Share of households incurring a rain induced loss]	(0.419)	(0.394)	(0.436)	
Observations	8570	3748	4034	

Standard deviations in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Table 3-1: Summary statistics

Non-labor market participating households display on average larger household sized with on average 6 members compared to 5.3 members across the participating households. Again, the mean difference is significant on any significance level. According to the summary statistics, labor time allocation seems to be significantly negatively affected by the farm size: The average farm size across the households not active in labor markets is significantly larger than the farm size of households who are active in the labor market, with on average 8.06 acres compared to 5.31 acres of farm size[6].

Smaller farm sizes are hypothesized to entail a higher production risk as a smaller farm surface provides fewer opportunities for crop diversification. Thus, farm size could be seen as an exogenous parameter of informal risk management. It also seems that labor time allocation is an instrument of the less professional farmers. To the extent that irrigation requires capital inputs and technology, households that are not active in labor markets dispose on average of more irrigable area than households that are active in labor markets, comparing a share of 55 to 45 per cent of irrigable farm surface for the respective subgroups. A similar picture turns out when it comes to physical capital employed in the agricultural production process: It is lower among the labor market participating households compared to the non-participating ones with on average INR 20,248 compared to INR 30,465 of capital stock value.

This part of the descriptive analysis is complemented by the revenue from farming, which amounts to INR 610,000 on average for the non-participating households and INR 340,000 for the labor market participating households respectively. In combination with smaller farm size, lower capital input and lower irrigable area shares, those who allocate labor time seem to be the type of households that are to a higher degree small-scale and subsistence farmers. This farmer type is more vulnerable towards rainfall variability as their smaller farms provide less potential for crop diversification and who have less opportunities to employ fertilizer, machinery or irrigation in the production process.

In addition, there is descriptive evidence that labor time allocation is also used as an ex post reaction towards rainfall variability. This is shown by the fact that the share of households that incurred a deficient rain related income loss is higher among the labor market participating households compared to the non-participating ones.

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[6] Compared to European farms, the average farm of this sample is a small holder farm. 6.66 acres correspond to almost 2.7 hectares. The median farm size in Germany in the year 2011 was between 100 and 150 hectares (Deutscher Bauernverband, 2016)

In the following part, the empirical specification will be presented to test the impact of risk –production and purchasing power uncertainty– on labor time allocation decisions.

3.3.2 Empirical specification

As it will be pointed out in the part on the empirical specification, the panel structure of the dataset cannot be used by employing models to correct for unobserved heterogeneity. Hence, a pooled ordinary least squares (OLS) model will be estimated and further specified in subsequent parts of this chapter.

As stated above, the effect of joint income uncertainty on labor allocation decisions will be tested using a pooled OLS model. The empirical model is given by expression (1):

$$farm\_days_{it} = \beta_0 + \beta_1 \times stdrain_i + \beta_2 \times stdwheat_i + \beta_3 \times stdrice_i + \Gamma' X + \epsilon_{it} \quad (1)$$

where $farm\_days_{it}$ is equal to the number of farm days except housework (farming and livestock rearing) in year t per individual. To account for the effects of farm income uncertainty and uncertainty about the purchasing power of income, the standard deviations of rainfall amounts and representative food prices have been included into the estimation. Due to the limited availability of food price data at the village level, it is not possible to integrate updating standard deviations of food prices into the regression model. This excludes standard panel data models as a constant standard deviation for a particular consumption good would vanish from every fixed effect regression model. To estimate the effect of price risk on labor time allocation, pooled models had to be applied. Using the standard deviation in the context of agricultural production risk might be problematic as this implicitly assumes that positive and negative deviations from the mean were equally harmful. This implicit assumption can be accepted with respect to rainfall variability as positive and negative deviations are equally harmful for agricultural activity. However, for robustness checks, other measures of rainfall variability such as the yearly deviations from the mean have been used as regressors. The results of this estimation similar time allocation effects and are available upon request.

$stdrain_i$ describes the standard deviation of rainfall levels in a specific village i. It is computed using a time series of rainfall data for the villages under study, spanning at least a period of seven years for every village. Thus, the production risk is measured on the village level and constitutes a constant value throughout the waves for every individual living in the same village. It is hypothesized that higher levels of standard deviations reflect higher farm production risks.

To separate the effects of farm profit and purchasing power uncertainty, a measure for uncertain consumer prices is used by considering representative food prices of basic commodities such as rice and wheat. Village prices were used according to the ICRISAT-terminology as non-subsidized shop prices at the local village trader.

$stdwheat_i$ describes the standard deviation of wheat prices at a specific village i, where four years of unsubsidized wheat prices at the village level have been aggregated to compute the standard deviation. The same has been made for another broadly available and typical consumption good, namely rice. This has been included by $stdrice_i$. Again, it is assumed that higher levels of standard deviation reflect higher consumption risks faced by the consumers.

Multicollinearity induced by a high correlation between regressors may influence the size of standard errors and hence the empirical inference (cf. Bekaert et al., 2009). As standard deviations of rainfall levels and food prices may be highly correlated with each other as well as standard deviations of food prices among each other, the standard deviations of food prices have been orthogonalized with respect to rainfall deviations and remaining food prices. Hence, an auxiliary regression according to (2) and (3) was performed for the staple foods rice and wheat:

$$stdwheat_i = \beta_0 + \beta_1 stdrain_i + \beta_2 stdrice_i + \epsilon_i \tag{2}$$

$$stdrice_i = \beta_0 + \beta_1 stdrain_i + \beta_2 stdwheat_i + \epsilon_i \tag{3}$$

The residuals of the auxiliary regression (2) and (3) have been used as regressors in (1). Next to the major explanatory variables, the matrix X contains several control variables, such as household size, age, education, physical ability, etc which will be introduced and justified in what follows.

Several studies point out the importance of age – included as $[age]$ – and education – included as $[yrs\_edu]$ – for labor market participation decisions of farm households as a measure of experience and the degree of formal training (cf. Mathse and Young, 2004, Mishra and Holthausen, 2002, Ruben and van den Berg, 2001, Abdulai and Delgado, 1999). These studies point out that the degree of labor market participation increases up to a specific age and decreases thereafter. Hence, the quadratic term of age [$age2$] will also be included in the analysis. In all subsequent specifications, the sample of individuals was restricted to individuals of at least nine years. Screening the data turned out that respondent's physical ability changed to the highest employable level at the age of around nine. Robustness checks have been performed, altering the age boarder. As the results changed only gradually, they will not be reported in the paper.

Another critical factor that has been identified to affect labor time allocation is gender (Abdulai and Delgado, 1999, Mishra and Goodwin, 1997). Gender specific off-farm labor supply decisions are interrelated between household members. This is why a joint off-farm labor supply equation will be estimated, integrating potential gender differences by a dummy variable.

Abdulai and Crole Rees (2001) describe that households in remote areas show less diversified income portfolios than households living closer to urban centers. Hence, it is hypothesized that large agglomerations provide a more diversified labor market and thus more potential employment alternatives besides farming. Thus, a measure of market distance has been included in the set of control variables to proxy job opportunities besides agriculture [$mrkt\_dist$].

Other variables that have been included into the analysis are physical ability [deg_ab], marital status [$married$] as well as farm size [$farm\_size$] and household size [hh_size]. As consumption price fluctuations could also be absorbed by an increase of own product consumption, it is also controlled for home consumption of produced goods. As production structures are highly heterogeneous, the regression will control for the value of consumption, hence the difference between gross value of own products and the income from farming. In addition, the amount of physical capital included in the production has been integrated as a further control variable.

In order to conduct robustness checks and to extend the analysis, labor market participation behavior will also be analyzed. For this purpose, a probit model of labor market participation will be estimated in the first step. In a second step, the labor supply function for those individuals that are active in the labor market will be estimated. This robustness check is being done to verify that farm time allocation and time allocated to labor markets are reciprocal decisions. The model to estimate the likelihood of labor market participation is given by equation (4):

$$Pr(Y = 1|X = x) = \beta_0 + \beta_1 \times stdrain_i + \beta_2 \times stdwheat_i + \beta_3 \times stdrice_i + \Gamma'X + \epsilon_i \qquad (4)$$

The dependent variable takes on the value of 1 if the considered individual reports at least one day of labor market participation in any year. The empirical model (4) contains the same measures of risk, either on the farm or the labor market level, as well as the control variables specified in the empirical model 1 above.
The model to estimate the extent to which an individual is active in the labor market is given by equation (5):

$$work\_days_{it} = \beta_0 + \beta_1 \times stdrain_i + \beta_2 \times stdwheat_i + \beta_3 \times stdrice_i + \Gamma' X + \epsilon_{ti} (5)$$

where $work\_days_i$ is equal to the number of work days of an individual employed in the labor market during a calendar year. The sample has been restricted to the group of individuals that exhibit positive labor market participation, and again, were at least nine years old.

3.4 Results

In the following section, the results of the pooled OLS estimation as well as of the probit model will be presented. As noted in the previous section, the dependent variables are the number of farming days as well as the number of workdays and the binary variable of labor market participation. Table 3-2 below summarizes the results of the estimation procedures and shows the estimated coefficients for the variables of interest. A focus of the analysis is made on the determination of paid activities to account for purely monetary risks induced by weather shocks and food price variability.
In regression (I), which comprises the whole sample of households, farm income variability increases the amount of time allocated towards the own farm significantly, everything else held equal. Hence, there is empirical evidence that farm labor input and rain are substitutes; a higher rainfall risk seems to be compensated by a higher labor input on the farm. The result also holds for the sub-group analyzed in regression (Ia) where households that – among other goods – cultivated rice or wheat, were excluded. Also in this subgroup, an increase in the rainfall risk increases the amount of time allocated towards the own farm.

	(I) *farm_days* Pooled-OLS	(Ia) *farm_days* Pooled-OLS	(II) *lmpart* Probit	(IIa) *lmpart* AME	(III) *work_days* Pooled-OLS
age	3.842***	4.447***	0.155***	0.0425***	8.919***
	(6.59)	(7.04)	(21.57)	(20.76)	(5.80)
age2	-0.0414***	-0.0473***	-0.00185***	-0.000507***	-0.102***
	(-6.02)	(-6.07)	(-24.13)	(-23.48)	(-6.36)
yrs_edu	-2.946***	-2.657***	-0.0126	-0.00344	4.775***
	(-5.20)	(-5.23)	(-1.19)	(-1.20)	(4.46)
farm_size	1.044*	1.299**	-0.0521***	-0.0143***	-2.270***
	(2.05)	(2.24)	(-5.51)	(-5.51)	(-3.05)
irriare	22.23***	18.26***	-0.396***	-0.108***	-11.36*
	(4.71)	(4.06)	(-4.89)	(-4.92)	(-1.91)
stdrain	13.49***	14.69***	-0.0496	-0.0163	-16.44***
	(18.13)	(21.44)	(-0.83)	(-0.84)	(-12.34)
stdrice	0.0511***	0.0750***	-0.00113***	-0.000308***	0.0361**
	(3.60)	(6.29)	(-2.87)	(-2.96)	(2.38)
stdwheat	0.204***	0.193***	-0.000153	-0.0000419	-0.100**
	(7.17)	(7.48)	(-0.12)	(-0.12)	(-2.50)
degab	37.82***	36.53***	0.641***	0.175***	11.70
	(6.17)	(6.06)	(5.81)	(6.50)	(0.79)
male	41.59***	42.13***	0.608***	0.167***	25.13***
	(3.86)	(3.65)	(4.64)	(5.01)	(4.36)
married	16.37***	16.19***	-0.168	-0.0461	-22.29***
	(4.64)	(4.70)	(-1.29)	(-1.28)	(-2.97)
mrkt_dist	2.203***	0.105	-0.0803***	-0.022***	-0.370
	(4.31)	(0.21)	(-2.67)	(-2.75)	(-0.33)
Observations	8570	7829	8054	8054	3816
R^2	0.334	0.341			0.193

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the number of farm days in the first two columns, a binary variable indicating positive labor market participation in column 3 and the number of labor market days for those who reported an active labor market participation in the last column. All regressions, except regression (IIa), contain village and year dummies.

Table 3-2: Regression results

As this first result seems to be in conflict with the standard perception of labor markets in risky surroundings, there is another plausible explanation for that observation: Rainfall shocks may translate into deteriorating labor market conditions. Taking the evidence by Walker and Ryan (1990) and the positive coefficient of farm production uncertainty, it is reasonable to conclude that labor market activity in rural areas may also be weather dependent. Hence, labor market opportunities deteriorate in drought years such that farm households have no other option but to increase farm time (cf. Rose, 2001, Kanwar, 1999, Walker and Ryan, 1990). In line with these findings, regression (III) finds that the amount of labor time allocated towards the labor market decreases in the rainfall risk, everything else held equal. Surprisingly, rainfall risks do not affect the decision to participate in labor market activities in a systematic way. This can be seen from regressions (II) and (IIa), which represent the probit model of labor market participation and the related average marginal effects (AME) respectively.

Food price volatility affects time allocation decisions in a way that is consistent with theoretical predictions: An increase in the standard deviation of rice [$stdrice$] and wheat [$stdwheat$] prices leads to an increase in the time allocated towards farming such that time resources are allocated away from the risky activity. One might oppose that rice or wheat producers would benefit from increasing prices. Hence, regression (Ia) excludes households that cultivated – among other goods –rice or wheat in any of the analyzed periods. It can be seen that the initial effect of food price volatility and its allocation effect for labor time persists in regression (Ia). Thus, an increase in the level of food price volatility increases the time allocated towards farming across the consumers of rice and wheat, everything else held equal. However, regression (Ia) reveals a more pronounced effect for the reallocation effect of rice price uncertainty compared to regression (I) which included the rice farmers. It is also remarkable that the reallocation effect induced by wheat is four times as large as the reallocation effect induced by rice price volatility.

Almost in line with these findings are the coefficients on rice and wheat price risks of regression (III). While an increase in the wheat price risk decreases the extent to which households become active in labor markets, an increase in rice price risks has a rather opposing effect. This result does not change between excluding households that partially produced wheat or rice and including them into the regression.

Other determinants of labor time allocation are revealed or confirm previous evidence. An individual's age [age] affects any allocation decision in a positive and significant way, everything else held equal. As the squared term [$age2$] is negative and significant in any of the regressions, there exists a maximum age after which the farm time allocation decreases. Using the results of regression (I) the peak is reached at an age of almost 46 years.

Education [yrs_edu] has a decreasing effect on the farm time allocation, everything else held equal. Even though there is no systematic effect of education on the probability of participating in the labor market, education increases the extent to which individuals supply labor to the labor market significantly, everything else held equal. An intuition for that result could be that more educated individuals opt out from agriculture and chose white-collar employment.
The farm size coefficient [$farm\_size$] is positive and significant in the farm time allocation regression (I). Hence, a larger farm size leads to an increase of the time allocated towards farming. Consequently, a larger farm size decreases the likelihood of being active in the labor market as well as it decreases the time allocated to labor market activities.
Another informal risk management tool could be irrigation. In order to account for the possibility that irrigation is potentially an informal risk management instrument, the percentage share of irrigeable area has been included as a control variable as [$irriare$]. It turns out that this variable has a large effect on the labor time allocation by increasing the time allocated towards farming whenever the percentage share of the irrigeable area increases, everything else held equal.
Dropping the variable from the regression does not change the size or significance levels of the remaining coefficients. An analysis of variance increasing factors does not reveal issues of multicollinearity. Thus, irrigation can be seen as one of the major drivers behind labor time allocation decisions. Doubts about this effect persist as the share of the irrigeable area could also be a sign of the degree of professionality in farming, hence catching up all effects that are related to the importance of farm and wage income. As leaving out the variable from the regression does not change the results substantially and there are no concerns with respect to multicollinearity and the set of control variables is broad, the coefficient on [$irriare$] will be reported nevertheless.
The degree of physical ability [$deg\ \_ab$] as well as being male [$male$] has strong and positive effects on all types of income generating activities. Compared to physically less able individuals, those who are physically strong allocate significantly more time resources towards farming and supplying labor to labor markets. The same is true for the dummy variable gender, which confirms gender differences in the intra-household work allocation.
Being married [$married$] increases the amount of time allocated towards farming whereas it decreases the extent of time allocated to labor markets.

Another interesting result relates to the market distance [$mrkt\_dist$]. As has been pointed out in the specification part, previous literature found that households living in more remote areas exhibit less diversified income portfolios and are less likely to participate in labor market activities. This result is supported by the analysis presented in this study. An increasing market distance leads to higher time allocations towards farming and decreases the likelihood of labor market participation significantly, everything else held equal. The effect of the market distance on the extent of labor supply, however, is not clear-cut; the direction of the effect is negative, however, the coefficient is insignificant.

To summarize, depending on the risk measure of farm income variability, food prices are crucial for the determination of farm time allocation towards agriculture. Depending on the underlying commodity and price constellation, labor time allocation changes with the riskiness of food price changes. The analysis has also shown that households are sensitive concerning real wage changes and adapt their labor time allocation in dependence of price changes.

3.5 Conclusions

The study presented in this chapter has shown that food price volatility has a significant influence on the time allocation of agricultural households. Previous studies took output price uncertainty and unemployment into account when conducting research on the effects of uncertain farm income on the labor time allocation decision by agricultural households. According to the present study, food price volatility is another factor that puts the income of consumer-producer households at risk by devaluing the purchasing power of wages. By estimating a pooled OLS regression model, the farm time allocation as well as the determinants of the labor market participation and the extent to which households allocate time resources towards labor markets have been determined. The results largely confirm the considerations with respect to labor market participation: Households reallocate resources away from the risky alternative and engage more in farming whenever food price volatility increases. Hence, the purchasing power risk of income is taken into consideration by the households under study when determining their labor time allocation. This result is also valid when the estimation excludes rice and wheat producers. The majority of households are primarily cash crop producers of sugarcane, whereas food crops such as rice and maize are – if produced at all – primarily produced for home consumption, for which the regression controlled.

Surprisingly, households do not reallocate time resources in the predicted way with respect to farm production uncertainty. The analysis revealed that the effect of an increase in the rainfall variability on farm time allocation is positive. Hence households reallocate more time resources towards farming whenever the agricultural rain fed production is becoming more risky. This has been explained by the interrelation between rainfall variability and labor market conditions; rainfall variability affects labor market opportunities in a negative way.

This study reveals important policy implications. Increased food price volatility in combination with agricultural production risk and agricultural labor market structures may force households to specialize in farming. Such a concentration in income-generating activities, however, is problematic because farm income is subject to weather outcomes. Thus, food price volatility forces households to concentrate their income sources and thereby increases vulnerability with respect to weather outcomes. Formal insurance products to ensure the income of farming households neglect the consumption risk of wage incomes, which forces individuals to alter their labor time allocation. Existing insurance products, such as index-based crop failure insurance, only ensure losses from agricultural activities whereas the income from off-farm work is entirely unprotected but periled by food price volatility. Thus, one potential countermeasure could be to more carefully consider the term *income* of farm households and to recognize that income is composed out of several sources. Hence, by enlarging the index variable of traditional index-based microinsurance with measures accounting for food price volatility would allow to trace the true income risk of farm households more appropriately. At the same time, enlarging the notion of income could also contribute to a greater demand for index-based insurance such that the vulnerability of farm households could be reduced. In addition, this would push the labor time allocation towards the optimal allocation, the one that would materialize without food price volatility. Thus, better eliciting the true income risks and enhancing the understanding of livelihoods and processes by which income is generated might be crucial for understanding the microinsurance demand of farming households.

Furthermore, the study provides implications for public policy: Labor markets have been identified as being decisive for risk coping. Consumption and production risk forces households to specialize in farming. Hence, one could conclude that measures to improve labor market access and diversity of labor market opportunities could have positive effects for the risk-management abilities of low-income households.

4 Income heterogeneity and index insurance demand[7] [8]

Abstract

Weather index insurance as a tool to insure the income of agriculturally active households has triggered extensive discussions in the literature. Despite the convincing theoretical argumentation, the demand for these products stays behind expectations. Several studies revealed effects impacting the demand for index insurance, such as liquidity constraints, basis risk, lack of understanding and trust in insurers and products alike. This paper takes a different perspective and hypothesizes that low demand is due to heterogeneous risk exposure towards weather variability among potential insured. The paper tests the impact of income heterogeneity as a measure of risk exposure on insurance demand and finds that risk exposure negatively affects insurance demand. In order to increase demand, it is concluded that product design should emphasize more the importance of income risk composition and exposure of potentially insured.

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4.1 Introduction

Agriculturally active low income households in least developed countries are facing a multitude of income risks such as weather related shocks, floods, droughts or storms, but also human or animal diseases or death of family members and even political risks and conflicts etc. Due to lacking social safety nets and governments which are unable to provide assistance in case of hardship, the materialization of most of these risks induces strong income fluctuations for large parts of the population.

Against this background, microinsurance as a hopeful instrument in the sphere of microfinance has evolved. Microinsurance shows some parallels with conventional insurance products, such as regular premium payments or conditional indemnity payments, although the terms and conditions are usually adapted to the target group (Churchill and McCord, 2012). Microinsurance products have to be affordable for low income households. Hence, the premium size is adapted to the financial strength of low income households. This implies that insurance companies need to cover similar administrative costs with comparably lower premiums if compared to a conventional insurance contract. For these reasons, index-based microinsurance products have evolved in order to insure systemic income risks of low income households.

Index-based microinsurance products are mainly characterized by the fact that the indemnity payment is triggered by an independent and non-influenceable variable that is closely correlated with the insured event. An example is the amount of rainfall in a specified time period in order to indicate a potential crop loss in the case of crop insurance. Whenever the index undercuts a given threshold, automatic indemnity payments are triggered and transferred to the insured without further state verification. In this sense, index-based microinsurance does not suffer from adverse selection as indemnity payments are usually lump-sum and insured dispose of no informational advantage with respect to their individual risk (Hazell and Hess, 2010). In addition, moral hazard incentives are minimized and costly state verification by the insurer is not necessary (Leblois and Quirion, 2013, Hazell and Hess, 2010, Breustedt et al., 2008). Surprisingly, despite the enormous risks threatening the incomes of agricultural households, the demand for index-based microinsurance products is lower than expected (Awel and Azomahou, 2015, Karlan et al., 2014, Cole et al., 2013, Norton et al., 2011, Hill and Robles, 2011, Giné et al., 2010, Giné and Yang, 2009).

Lacking demand and the identification of demand driving factors have been subject to widespread research. Eling et al. (2014) provide an extensive review of demand studies. Several studies revealed counterintuitive demand patterns such as decreasing demand probabilities in the degree of self-reported risk aversion (Dercon et al., 2011, Giesbert et al., 2011, Giné et al., 2008). This has widely been interpreted as a lack of trust, such that those with higher degrees of self-reported risk aversion trust less in insurers and products alike and thus show lower insurance adoption rates.

A product inherent characteristic of index-based microinsurance products is basis risk. This risk describes the possibility that insured households receive an indemnification without experiencing a loss or vice versa, experiencing a loss but receiving no indemnification. Several studies point out that the extent of basis risk impacts on demand in a negative way (Clarke, 2016, Brick and Visser, 2015, Mobarak and Rosenzweig, 2012, Giné et al., 2008).

Recent insights from behavioral economics imply that low demand may also be due to compound risk aversion. Index insurance contracts can be interpreted as compound lotteries. In experiments, Elabed and Carter (2015) found that low-income households are unable to derive the actuarial equivalent simple lottery of a compound lottery and therefore refuse to buy an index insurance contract. They interpreted that behavior as compound risk aversion.

None of the demand related literature cited above analyzed the interrelationship between informal risk management in the form of labor time allocation and formal insurance demand. Controlling for other identified demand factors, this gap will be closed and the effect of labor time allocation and resulting heterogeneity in the income composition on insurance demand will be empirically analyzed in this paper. For this purpose, it is argued that low demand for index-based weather insurance may be observed due to varying degrees of risk exposure towards rainfall variability as a consequence of informal risk management: Risk averse households apply informal risk management in the form of labor time allocation (Bandyopadhyay and Skoufias, 2015, Rose, 2001, Kanwar, 1999, Mishra and Goodwin, 1998, Mishra and Goodwin, 1997). In consequence, some households rely more on farm income while others rely more on a combination of farm and non-agricultural labor market income. Thus, depending on the income composition, weather insurance written on rainfall variability has a varying return for different households as the correlation between index and income realizations might differ.

Hence, it is straightforward to expect that households earning higher income shares from non-agricultural labor have reduced incentives to buy index-insurance products written on rainfall variability due to a lower risk exposure towards rainfall fluctuations. This adds another interpretation of the relation between risk aversion and formal insurance demand: More risk averse households apply more informal risk management and have more diversified income structures. Due to the higher degree of informal income protection, formal insurance contracts exert a lower risk reducing effect on these households. Thus, the negative effect of risk aversion on insurance demand could also be explained by a higher activity level in informal risk management by the more risk averse individuals and a resulting higher degree of informal protection.

The remainder of the paper is organized as follows: In section 4.2, a literature review on identified demand determinants will be given. Section 4.3 presents the data and the empirical specification. Section 4.4 presents the results of the estimations and section 4.5 concludes.

4.2 Literature review

The objective of this study is to analyze the relationship between informal risk-management and formal insurance demand with a particular emphasis on risk exposure and labor time allocation. In this section, the literature on the main demand determinants for index-based microinsurance products will be presented.

A product inherent characteristic of index-based microinsurance products is that indemnity payments are determined by observing an index that is closely correlated with the volatility of the underlying insured asset. In the case of drought insurance, the amount of rainfall within a specific area and time period is an indicator whether households living in the surrounding of a rainfall gauge incurred a rainfall induced income loss. The risk that index realizations and outcomes at the household level deviate from each other is the basis risk and its occurrence has been found to have a negative effect on insurance demand (Clarke, 2016, Brick and Visser, 2015, Mobarak and Rosenzweig, 2012, Skees, 2008, Giné et al., 2008). Basis risk –which could also be understood as a contract non-performance risk– can prevent households from buying full-insurance, even if the premium is fair (cf. Clarke, 2016, Schlesinger and Schulenburg, 1987).

The size of basis risk is mainly determined by the distance between the farm and the related rainfall gauge. As rainfall realizations are a regional event, larger distances imply a larger prediction bias using the rainfall information from a specific rain gauge to predict loss experience at the farm level. Discussed countermeasures in the presence of basis risk comprise to subsidize the premium or to increase the density of rainfall gauges (Clarke, 2016). Another countermeasure is to use rainfall indices at different geographical levels to thereby increase the correlation between index and farm level outcome (Elabed et al., 2013).

Heterogeneity in the income composition resulting from informal risk management can be seen as a particular form of basis risk as the correlation between index and income volatility decreases: Rainfall variability is a predictor of the productivity in farming but not in non-agricultural labor markets. Hence, households with a diversified income profile and relatively higher income shares from non-agricultural labor display a lower correlation between their income volatility and the underlying index compared to households that mostly rely on farming income. This corresponds to the definition of basis risk (cf. Clarke, 2016).

Prior studies emphasized the importance of liquidity constraints and premium sizes to be decisive for microinsurance demand (Cole et al., 2013, Mobarak and Rosenzweig, 2012, Dercon et al., 2011). Other studies found that the take-up rate increases substantially if other modes of payment are chosen, such as contract farming or work programs in exchange for insurance coverage (Tadesse et al., 2017). This argument is plausible as premium payments compete with other expenditures, such as seeds, fertilizer, machinery or the like taken out by the household. Although it is evident that budget constraints are not the only reason to explain take-up decisions, they have been identified as being decisive for insurance purchase.

Risk aversion has been found to have a negative effect on insurance demand (Dercon et al., 2011, Giesbert et al., 2011, Giné et al., 2008). Conventional wisdom assumes that more risk averse individuals would purchase more insurance coverage (Pratt, 1964). However, in the context of LDCs, Giesbert et al. (2011) explained the negative relationship by a lack of trust: Those individuals that are more risk averse are more suspicious about new and unknown products. In the case of insurance, a trust related factor might also be that an insurance contract is nothing but a promise to indemnify future losses under predefined conditions while the premium has to be paid on the spot. Thus, more risk averse individuals distrust the insurance provider with a higher likelihood and show therefore lower adoption rates.

A second story on the relation between risk aversion and insurance demand is added by this study: Risk aversion stimulates informal risk management activities and thereby decreases the incentive to buying formal insurance contracts.

Another factor that has been identified as a crucial determinant for the participation in financial markets is financial literacy. Hilgert et al. (2003) showed that there is a positive impact of financial literacy on the quality of financial decisions, which have a short term character and actions that have a longer lasting planning horizon. Financial literacy has also been shown to have positive impacts on financial and stock market participation or on precautionary savings (Bassa Scheresberg, 2013, van Rooij et al., 2012, Christelis et al., 2010, Kimball and Shumway, 2006). In these studies, however, financial literacy is not generally and systematically linked with school education.

Furthermore, it has been shown that financially more literate individuals do rely more likely on formal credit relationship and are better able to cope with macroeconomic shocks (Klapper et al., 2013). In addition, financially more literate households are less likely to enter into high-interest rate debt contracts and to accumulate more wealth in general (Lusardi and Mitchell, 2007). Summing up the evidence on financial literacy, forecasts on the household's insurance demand is ambiguous: On the one hand, the likelihood of making sound decisions increases in the degree of financial literacy, which could be an argument to hypothesize that insurance demand increases with the degree of financial literacy. On the other hand, financially more literate households are also more likely to engage in precautionary savings which could serve as a substitute to formal insurance contracts. Applied to the microinsurance context, Cole et al. (2013) found positive effects of insurance training and education modules on insurance demand.

The demand factors presented above constitute the most important determinants of formal insurance demand. Further potential demand factors will be developed in the empirical specification in section 4.3.

4.3 Data & Empirical Specification

After outlining the rationale for an unconsidered source of basis risk induced by informal risk management and resulting income heterogeneity, the data and empirical specification will be presented in order to test the hypothesis that the degree of non-agricultural labor income has an effect on insurance demand.

The data set employed here is taken from the study of Cole et al. (2013). The cross-sectional survey from the year 2006 covers a total of 1,047 land-owning households in Andhra Pradesh, India. Thus, every household perceives potentially a non-negative amount of income stemming from agricultural activity. At the same time, income profiles of households under consideration display sufficient heterogeneity to analyze the impact of income heterogeneity on index insurance demand. After adjusting the data, a total of 893 households persist.

In what follows, the empirical analysis tries to reveal further empirical evidence for the argument that careful risk and exposure assessment as well as a consistent design of underlying indices might be an appropriate solution to increase demand for index based microinsurance and to enhance the transition from informal to formal insurance solution.

4.3.1 Drought insurance characteristics

The drought-insurance product under study is marketed by the non-governmental organization BASIX and is sold by *Livelihood Services Agents* in villages in Andhra Pradesh, India. The product is underwritten by ICICI Lombard, an Indian financial service provider, which is well recognized. The product divides the Monsoon season into three phases of 35-45 days length each. Policies written on the first two phases cover the risk of lacking rainfall whereas the last phase policy covers excessive rainfall in the immediate pre-harvesting stage. Threshold levels have been determined using recognized crop growth models. Households willing to insure a whole Monsoon season therefore would have to buy three policies. The amount of rainfall and the payoff calculation is based on nearby governmental rainfall stations or automated rain gauges by an external operator (Cole et al., 2013).

Figure 4-1 given below represents the indemnity function for the drought coverage phases.

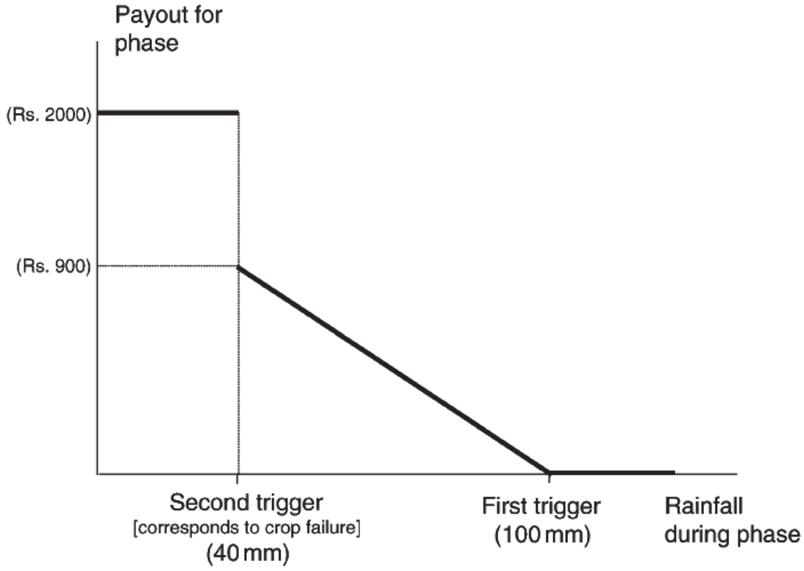

Figure 4-1: Indemnity function of Phase 1&2 drought insurance[9]

The indemnity function is linear between the upper (strike) and the lower (exit) threshold level and increases in the amount of lacking rainfall for the first two phases of the Monsoon season. Thus, for every millimeter that rainfall falls short from the strike level, the contract pays a constant amount of INR 10 to the policyholder. Whenever rainfall undercuts the exit level, crop failure is sufficiently likely and the contract pays out a fixed amount of INR 1.000 per policy, but still irrespective of the individual loss experience of a particular farmer.

Threshold levels have been calculated using crop growth models for the major production cash crops in the region, castor and groundnut (Giné et al., 2008).

In the third phase of the Monsoon season, a policy pays INR 10 for every millimeter that rainfall exceeds the strike level and pays out INR 1.000 whenever rainfall exceeds the exit level (not shown in Figure 4-1 above). Contracts were designed such that one policy covers the risk of one acre of land. Average land holdings were about 6.31 acres. Combined premiums for all three phases of the Monsoon season ranged between INR 260 and INR 340 depending on the district of sale (Cole et al., 2013)[10]. The payoff structure seems to be problematic as realized rainfall levels slightly above the exit level are significantly less indemnified than rainfall levels

[9] Source: Giné et al. (2008)

[10] The average income is equal to INR 59,656 (1,324 current US-$) per year. Maximum payout of INR 1,000 correspond to 22.20 US-$ (current), while the premium payment equals to INR 340 or 7.55 US-$ (current). Premium payments are thus equal to 0.57 % of the average annual household income.

slightly below the exit level although the probability of crop loss should not differ drastically. However, data does not allow controlling for the payoff structure in the empirical demand analysis.

Households were free to buy any number of contracts to thereby adapt the coverage according to their rainfall risk. However, the demand variable is rather a binary variable. Almost none of the households purchased more than one contract. This provides evidence that households being unfamiliar with the product concept tried the product rather than insuring their risk adequately. According to Cole et al. (2013), 60 % of households bought Phase 1-contracts, providing coverage against lacking rainfall.

To summarize, the product covers losses that are induced by rainfall variations. By construction, it entirely neglects income that is derived from non-agricultural labor market activity and is thus suitable to examine the hypothesis of wage-induced heterogeneous risk exposure as a factor impacting on insurance demand.

4.3.2 Summary Statistics

The objective of the study is to research the relationship between informal risk-management and formal insurance demand with a particular emphasis on risk exposure. In this section, the summary statistics will be presented.

Table 4-1 below depicts the summary statistics. The first column reflects the values for the entire sample whereas the second and third column differentiate between policy and non-policy holding households respectively. The fourth column depicts the significance levels of a two-sided t-test of mean differences between insured and non-insured households and column E reflects the expected effect on insurance demand probabilities.

Drawing on the effect of risk exposure measured by the share of non-agricultural wages, it can be seen that among the insured households, the average share of non-agricultural wages was lower (11% compared to 18 % among the non-insured households). Insured households relied to a larger extent on activities where rainfall determines productivity than non-insured households. Hence, there is descriptive evidence that risk exposure with respect to rainfall variability measured by the share of non-agricultural wages, has a negative impact on demand.

	(A) Full sample	(B) Insured households	(C) Non-insured households	(D) t-test for mean differences	(E) Expected demand effect
yrs_edu	3.93	4.14	3.83		+
[Years of schooling]	(4.819)	(5.117)	(4.686)		
hhsize	6.29	6.48	6.21		o
[Household size]	(2.846)	(2.914)	(2.815)		
muslim	0.02	0.02	0.03		o
[Percentage share]	(0.155)	(0.148)	(0.158)		
sexhead	0.94	0.95	0.94		o
[male headed households, %]	(0.230)	(0.223)	(0.233)		
age_head	48.83	49.16	48.69		o
[Age of household head]	(12.11)	(12.11)	(12.12)		
group_add	0.74	0.80	0.71	*	+
[Share of self-help group member]	(0.619)	(0.621)	(0.617)		
riskav	0.56	0.52	0.58	***	-
[Measure of risk aversion]	(0.259)	(0.268)	(0.252)		
lcultirrpct	0.43	0.48	0.41	**	+
[% share of irrigeable farm size]	(0.434)	(0.437)	(0.430)		
d_highreward	0.31	0.65	0.16	***	+
[Share of high reward receivers]	(0.461)	(0.479)	(0.367)		
Electrified household	0.65	0.68	0.64		
[%]	(0.478)	(0.468)	(0.482)		
inc_total	59,656.00	62,467.04	58,450.63		+
[Household income, INR*]*	(103,312.9)	(94,512.9)	(106,914.5)		
farm income share	0.42	0.44	0.41		
[%]	(0.349)	(0.346)	(0.351)		
wsna	0.16	0.11	0.18	***	-
[Share of non-agricultural wages]	(0.292)	(0.247)	(0.307)		
ins_other	0.83	0.91	0.79	***	+
[Share of households possessing other insurance products]	(0.379)	(0.291)	(0.406)		
Observations	893	268	625		

Mean values, standard deviations in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Table 4-1: Summary statistics

With respect to liquidity constraints, one can observe that among the insured households, 65 % had received a high random cash reward of INR 100 compared to 16 % among the non-policyholders in exchange for a short training session on index-based microinsurance. In sum, 700 randomly chosen households of the sample received a random cash reward of either INR 25 or INR 100. Thus, the descriptive analysis supports the previous literature in identifying liquidity constraints as decisive for insurance take-up. Cole et al. (2013) raise the concern that this could be due to a felt obligation of gift exchange: Those, who received a subsidy could have felt forced to buy a policy. Thus, in the subsequent analysis, total household income instead of the reward information will be used as a measure of liquidity constraints.

Among those, who opted for insurance, the average risk aversion measure[11] amounts to 0.52 whereas the same number equals 0.58 among the non-insured. This is basically in line with prior research that found a negative relationship between insurance demand and risk aversion and explained this by a lack of trust into insurers and products alike (Dercon et al., 2011, Giesbert et al., 2011, Giné et al., 2008).

Irrigation could be seen as a potential substitute for drought insurance. The descriptive data analysis provides a counterintuitive result: Among insured households, 48 % had good irrigation possibilities whereas the same number amounts to 41 % among those who are not insured.

Further informal risk management factors and a potential informal risk management instrument is the number of household members. Households with more members have better abilities to sending out family members to other cities and places to thereby making use of their labor force. The data, however, provides counterintuitive evidence: Among insured households, the average family size equals 6.48 members, whereas the average non-insured household comprises 6.21 members. Hence, it is expected that the family size does not have an effect on the insurance take-up decision.

A positive demand effect is expected from product experience: Among those, who have drought insurance, 91 % percent of households had also experience with other insurance products, whereas 79 % of the households not having a drought insurance contract reported experience with this type of financial products.

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[11] The measure of risk aversion has been constructed along the methodology of Binswanger (1980) and has been measured at the beginning of the Monsoon season 2006. Individuals choose from a menu of different lotteries that entail two different outcomes where the final payoff realization will be determined by a coin toss. The lottery is played against real money. Hence, a respective household trades expected payoffs against payoff variance, meaning that a higher expected payoff of a lottery is paid by a higher variance of the payoffs. The assigned value of risk aversion thus corresponds to the slope of that exchange function. Higher values thus indicate a higher degree of risk aversion.

Another factor that has been identified as a crucial determinant for the participation in financial markets is financial literacy. In the present study, descriptive data analysis reveals positive impacts of the general level of schooling as a proxy for financial literacy on insurance demand: Insured households show on average 4.14 years of schooling whereas non-insured households experienced 3.83 years of schooling. As Cole et al. (2011) point out, equalizing financial literacy and school education might be inappropriate in the Indian context. Thus, Table 4-2 in the results section will present estimations using the level of school education as a proxy for financial literacy. Table 4-3 will then use an explicit measure of insurance skills where respondents have been asked to show that they understand the concept of probabilistic insurance in general.

4.3.3 Empirical specification

In order to test the hypothesis of risk exposure possibly impacting on insurance demand, a probit model in three different specifications will be estimated. As none of the clients purchased more than one contract, demand and coverage data coincide and the dependent variable is binary. The empirical models are specified as follows:

$$\Pr(y = 1|X = x) = \alpha_0 + \beta_1 \times wsa_i + \beta_2 \times dfrg_i + Z \times \gamma + \epsilon_i \quad (6)$$

$$\Pr(y = 1|X = x) = \alpha_0 + \beta_1 \times wsna_i + \beta_2 \times dfrg_i + Z \times \gamma + \epsilon_i \quad (7)$$

$$\Pr(y = 1|X = x) = \alpha_0 + \beta_1 \times wna\_pc_i + \beta_2 \times dfrg_i + Z \times \gamma + \epsilon_i \quad (8)$$

where the dependent variable is a binary variable, taking on the value of 1 if the respondent had a drought insurance policy for at least one phase. Z is a $n \times k$ matrix of control variables and γ a $k \times 1$ vector of coefficients related to the control variables.

Data does not allow distinguishing between different phase policies; whether the respondent bought drought or excessive rainfall cover. However, this is not seen as problematic as the argument of risk exposure holds for both cases of lacking or excessive rainfall.

The variable wsa –the overall wage share from agricultural and non-agricultural labor– is one measure of the risk exposure and is computed according to (9):

$$wsa_i = \frac{Agricultural\ wages + Nonagricultural\ wages}{Farm\ profits + Agricultural\ wages + Nonagricultural\ wages} \quad (9)$$

By construction, the variable takes on values between 0 and 1.

$wsna$ –the share of wages from non-agricultural labor– is constructed in a similar manner and is given by (10):

$$wsna_i = \frac{Nonagricultural\ wages}{Farm\ profits + Agricultural\ wages + Nonagricultural\ wages} \tag{10}$$

Again, the variable takes on values between 0 and 1. The only difference with respect to (9) is that (10) only uses the amount of non-agricultural wages in the nominator.

In a third specification, the level of non-agricultural wages per capita [wna_pc] has been included into the model. It is defined by (11):

$$wna\_pc_i = \frac{Nonagricultural\ wages}{Household\ size} \tag{11}$$

All empirical models specified by equations (6)-(8) contain a measure of conventional basis risk by including the distance from the rain gauge into the analysis [$dfrg$]. All models use clustered standard errors where clustering has been performed on the village level. The dataset contains data from 37 villages.

With regards to the control variables contained in γ, a measure of risk aversion has been integrated [$riskav$] constructed along the methodology of Binswanger (1980). Higher values indicate higher levels of risk aversion.

In order to control for the impact of budget constraints, the variable inc_total is integrated into the analysis which measures the overall income level stemming from farming and supplying time to labor markets.

Trust issues have been integrated into the analysis in the following way: The variable ins_other has been included, taking on a value of 1 if the household purchased also other insurance contracts. The fact that a household also purchased other insurance contracts signals that he understands and trusts this concept. Hence, awareness and trust are equalized and integrated into the analysis.

In order to measure the degree of informal insurance coverage through self-help groups or communities as a potential substitute for formal insurance, the variable $group\_add$ has been included. It is constructed as a dummy variable and takes on the value of 1 if the respondent reported to be a member of a self-help group or community. On the one hand, it is questionable whether these self-help groups indeed constitute a risk pooling across individuals. However, the fact that an individual is part of a social group is considered to be an indicator of whether the particular household is socialized or rather isolated and may receive help of any kind in the case of a loss event. Moreover, self-help groups are considered to enable information flows such that members could spread information about the advantages of insurance and thereby stimulate the insurance demand of other group members.

Irrigation could reduce the vulnerability towards rainfall variations. Hence, irrigations and and drought insurance are considered to be potential substitutes, such that a higher share of irrigable area could lead to a lower probability of insurance purchase. Hence, the percentage of irrigable land has been included into the vector of control variables [$lcultirrpct$]. It measures the percentage share of the overall farm size that can be irrigated.

In order to account for imitation and peer effects, mean pay-outs on the village level of prior pilot study years in 2004 and 2005 have been integrated into the analysis as well [$mean\_payouts$].

Further control variables comprise a measure of financial literacy, proxied by the dummy variable [$d\_highedu$] taking on the value of 1 whenever school education of household heads is secondary school or higher. As there exist doubts whether schooling levels are a good proxy for financial literacy, an explicit measure of probabilistic insurance skills has been introduced in the estimation by integrating the variable [ins_skill]. Respondents were asked to answer questions on the basic principles of index insurance, such as to determine whether they would receive a payout given a hypothetic rainfall level. The results for this estimation are reported in Table 4-2, again for all measures of income heterogeneity.

4.4 Results

Table 4-2 represents the estimation results and coefficients of the probit model estimation. The dependent variable is equal to 1 if the household had at least one insurance contract. Column 1, 3 and 5 correspond to the equation (6), (7) and (8) whereas column 2, 4 and 6 depict the AME of the respective regressions. Risk exposure is modelled by the share of overall wage earnings in regression I or as the share of wage earnings that are not related to agriculture (Regression II) and in per capita terms (Regression III).

	(I) *ins_lev* Probit	(Ia) *ins_lev* AME	(II) *ins_lev* Probit	(IIa) *ins_lev* AME	(III) *ins_lev* Probit	(IIIa) *ins_lev* AME
wsa	-0.208 (-1.15)	-0.0668 (-1.14)				
wsna			-0.383** (-2.05)	-0.123** (-2.04)		
wna_pc					-0.0000350** (-2.21)	-0.0000112** (-2.20)
d_highedu	0.121 (0.91)	0.0389 (0.91)	0.139 (1.07)	0.0446 (1.07)	0.135 (1.03)	0.0433 (1.03)
age_head	0.00495 (1.00)	0.00159 (1.00)	0.00506 (1.02)	0.00162 (1.01)	0.00488 (0.99)	0.00156 (0.99)
riskav	-0.423** (-2.31)	-0.136** (-2.33)	-0.437** (-2.36)	-0.140** (-2.37)	-0.458** (-2.39)	-0.147** (-2.40)
inc_total	-0.000000239 (-0.51)	-7.70e-08 (-0.51)	-0.000000139 (-0.28)	-4.44e-08 (-0.28)	1.37e-08 (0.03)	4.38e-09 (0.03)
ins_other	0.418*** (2.83)	0.134*** (2.90)	0.441*** (3.04)	0.141*** (3.12)	0.469*** (3.30)	0.150*** (3.40)
dfrg	0.0110 (0.42)	0.00352 (0.42)	0.0135 (0.52)	0.00432 (0.53)	0.0137 (0.56)	0.00437 (0.56)
mean_payouts	0.542* (1.91)	0.174** (1.99)	0.542* (1.96)	0.174** (2.04)	0.555** (2.09)	0.178** (2.18)
lcultirrpct	-0.0306 (-0.30)	-0.00985 (-0.30)	-0.0218 (-0.21)	-0.00698 (-0.21)	-0.0217 (-0.21)	-0.00696 (-0.21)
group_add	0.0499 (0.53)	0.0160 (0.53)	0.0498 (0.53)	0.0160 (0.53)	0.0500 (0.52)	0.0160 (0.52)
Observations	885	885	885	885	893	893

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in all regressions is the dummy variable *ins_lev* taking on a value of 1 if the respondent had at least a policy for one Monsson phase. All regressions, except regression (Ia, IIa and IIIa) contain village dummies.

Table 4-2: Regression results I

In regression (III), income heterogeneity has been modelled using the level of non-agricultural wages per capita. All coefficients of income heterogeneity show a negative sign such that the likelihood of purchasing insurance decreases with the importance of wage earnings in household income, everything else held equal.

However, only the coefficients of non-agricultural wages and per capita wages are significant on the five percent level whereas the overall wage share coefficient is insignificant. This could be explained by the fact that rainfall predicts productivity in agriculture –self-employed or as a laborer– whereas there is no systematic relationship with the productivity of non-agricultural activities. Hence, there is empirical evidence that a higher wage share or per capita level of non-agricultural wages translates into a lower likelihood of purchasing rainfall insurance, everything else held equal.

A household's schooling level, measured in the dummy specification has a positive but insignificant effect on the demand decision. As the results stay unaffected whether schooling is measured in the dummy specification or using the years of schooling, the years of schooling specification will not be reported here.

Risk aversion affects the likelihood of purchasing insurance in a negative way, holding everything else constant. Thus, the more risk averse a household is, the less likely he will be buying drought insurance. This effect is significant on the five percent level. Decreasing likelihood of insurance purchase in the degree of risk aversion is in line with prior research. It is argued that more risk-averse households are more cautious about the new concept of drought insurance. At the same time, the empirical results support the interpretation that more risk averse households engage more in informal risk management and are thus better protected, even without formal insurance.

Trust into the concept of insurance increases the likelihood of buying drought insurance massively, measured by the variable ins_other: Having other insurance products has strong and positive effects on drought insurance demand, everything else held equal. This result holds on any significance level and is in line with prior research.

The affiliation to social groups is hypothesized to increase the likelihood of purchasing drought insurance (Cai et al., 2011). This is confirmed in the positive $group\_add$ coefficient. However, the coefficient turns out to be insignificant in any of the regressions.

Prior pay-out experiences seem to be an important driver of insurance demand: To experience that the product triggers pay-outs in prior years and their magnitude have a strong inciting effect to buy the product. This has also been found by other authors in similar settings (Cole et al., 2014). Higher mean pay-outs in prior years in a village increase the probability of insurance demand to a large extent, everything else held equal. Furthermore, the effect is highly significant in all regressions. Therefore, positive pay-out experiences are considered to be one of the major drivers of insurance demand.

There is no empirical evidence that insurance and irrigation are substitutes as the coefficient of the variable *irriare_pct* is positive, close to zero and insignificant on any significance level.

	(IV) *ins_lev* Probit	(IVa) *ins_lev* AME	(V) *ins_lev* Probit	(Va) *ins_lev* AME	(VI) *ins_lev* Probit	(VIa) *ins_lev* AME
wsa	-0.215 (-1.21)	-0.0688 (-1.20)				
wsna			-0.380** (-2.03)	-0.121** (-2.01)		
wna_pc					-0.0000339** (-2.16)	-0.0000108** (-2.14)
ins_skill	0.166*** (2.63)	0.0531*** (2.63)	0.168*** (2.63)	0.0536*** (2.62)	0.171*** (2.68)	0.0545*** (2.67)
age_head	0.00475 (0.89)	0.00152 (0.89)	0.00474 (0.88)	0.00151 (0.88)	0.00454 (0.86)	0.00145 (0.86)
riskav	-0.366** (-1.98)	-0.117** (-1.99)	-0.382** (-2.04)	-0.122** (-2.05)	-0.401** (-2.08)	-0.128** (-2.08)
inc_total	-0.000000247 (-0.53)	-7.91e-08 (-0.53)	-0.000000139 (-0.28)	-4.43e-08 (-0.28)	6.09e-09 (0.01)	1.94e-09 (0.01)
ins_other	0.418*** (2.77)	0.134*** (2.86)	0.442*** (2.99)	0.141*** (3.09)	0.471*** (3.25)	0.150*** (3.37)
dfrg	0.00337 (0.13)	0.00108 (0.13)	0.00550 (0.21)	0.00176 (0.21)	0.00578 (0.23)	0.00184 (0.24)
mean_payouts	0.312 (1.07)	0.0996 (1.09)	0.306 (1.06)	0.0978 (1.09)	0.317 (1.14)	0.101 (1.17)
lcultirrpct	-0.0449 (-0.41)	-0.0144 (-0.42)	-0.0334 (-0.30)	-0.0106 (-0.30)	-0.0320 (-0.28)	-0.0102 (-0.28)
group_add	0.0652 (0.69)	0.0208 (0.69)	0.0657 (0.70)	0.0210 (0.70)	0.0669 (0.70)	0.0213 (0.70)
Observations	885	885	885	885	893	893

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in all regressions is the dummy variable *ins_lev* taking on a value of 1 if the respondent had at least a policy for one Monsson phase. All regressions, except regression (IVa, Va and VIa) contain village dummies.

Table 4-3: Regression results II

Other effects that have been considered as important in the literature are liquidity constraints. In the specification of regression (I) through (VI), the total income level has been used as a measure of liquidity constraints. The related coefficients are close to zero and insignificant such that it is concluded that liquidity constraints do not exert a systematic influence on insurance demand in this sample. However, if the reward variable is introduced as a measure of liquidity constraints, this exerts a positive and significant influence on the insurance demand. Despite the fact that Cole et al. (2013) emphasize that high cash rewards have been attributed randomly, the reward variable is negatively correlated with risk aversion. Due to concerns about multicollinearity, the doubts about a simple gift exchange and the enormous coefficient size, the variable is left out as a measure of liquidity constraints.

Table 4-3 reports the estimation results with the modified measure of financial literacy. It can be seen that the direction of income heterogeneity effects on insurance demand remains unchanged. However, the estimation results confirm the conclusion drawn by Cole et al. (2011) that there is no systematic relationship between the schooling level and financial literacy. In our sample, the knowledge of probabilistic insurance increases the likelihood of purchasing drought insurance substantially, holding other effects constant.

In order to take a closer look at the marginal effects, the AME at representative values of the variable of interest – the wage share of non-agricultural wages – has been plotted and depicted in Figure 4-2 below.

It can be seen from Figure 4-2 that the positive marginal effect of higher mean payouts decreases as the share of non-agricultural wages increases. Hence, households that show a relatively higher degree of income diversification are decreasingly incentivized to buy drought insurance by observing higher mean payouts.

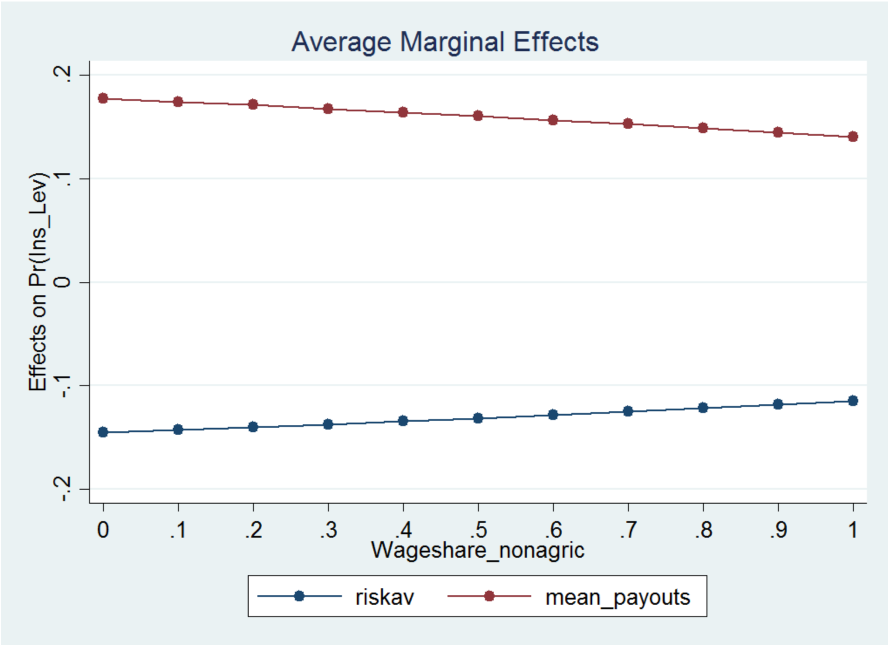

Figure 4-2: AME at representative values I

A similar reasoning applies to the degree of risk aversion: The more the income portfolio is diversified, i.e. the share of non-agricultural wages increases, the more the demand decreasing effect of risk aversion tends to zero. Hence, comparing an individual that is fully employed in agriculture and an individual that perceives 80 % of income from non-agricultural labor, the demand probability is almost two percentage points lower with the latter, everything else held equal.

Figure 4.3 depicts the same picture, now gradually changing the level of non-agricultural wages per capita. The same observations can be made although the change in marginal effects is more pronounced.

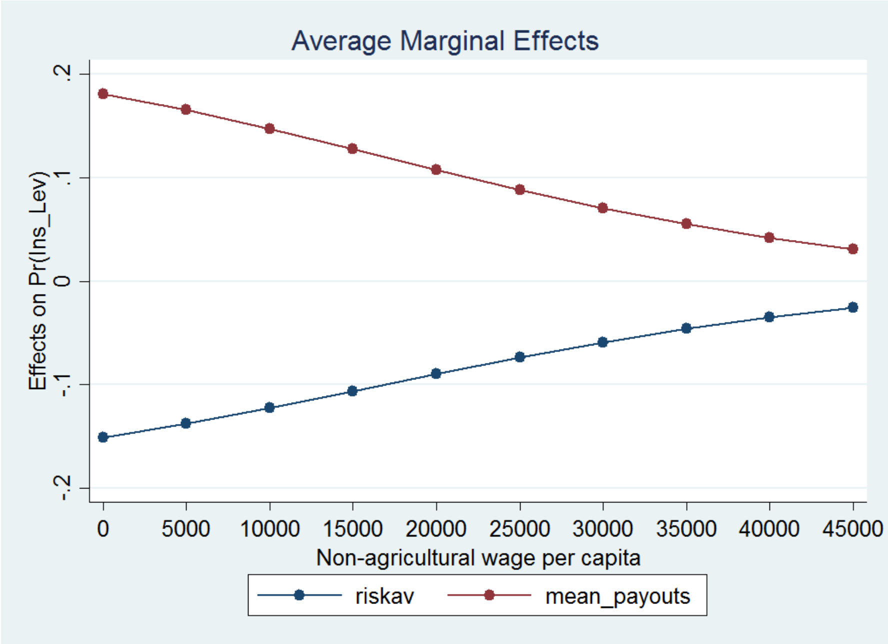

Figure 4-3: AME at representative values II

4.5 Conclusions

The study presented here investigated the impact of income heterogeneity and risk exposure on index-based microinsurance take up. It was hypothesized that rainfall variability predicts agricultural productivity, whereas there is no systematic relationship with productivity outside of agriculture. Hence, individuals perceiving a higher income share from activities not related to agriculture are faced with a lower risk exposure towards variations in rainfall amounts and show therefore a lower correlation between income variability and index realizations. This lowers the possible return from buying index insurance and thus decreases the incentives to buy the product.

The analysis has shown that formal insurance demand decreases as the degree of risk exposure decreases, where risk exposure towards rainfall variability was measured by the income share of non-agricultural wages. Using a dataset of smallholder farmers in Andhra Pradesh, there is empirical evidence for the mentioned hypothesis: The more income a household perceives from non-agricultural activities, the lower is the probability that he purchases drought insurance, holding other effects constant.

Other results of the existing literature in determining the demand for formal insurance were confirmed by the presented study: Risk aversion, trust and previous payouts as well as income heterogeneity are the major drivers behind insurance demand. Financial literacy exerts a significant effect on insurance demand as well. However, equilibrating school education and financial literacy turned out to be inappropriate.

In addition, there is empirical support for a further interpretation of risk aversion as a demand driving factor in insurance take up. Not only do more risk averse individuals trust less into insurance companies, but there is also evidence that risk aversion affects the decision to exert informal risk management positively. A higher degree of informal risk management reduces the incentive to buy formal insurance and thus results in lower take up rates.

Policy implications can be drawn with respect to product design which should more carefully consider income generating processes and also the utilization of income. Index insurance works best where the income risk and the risk exposure is homogenous. What has been shown by the analysis is that diversified income structures lead to a decreasing demand probability. Hence, one potential solution would be to redesign index variables that trace income composition or usage more closely in order to increase the correlation between index and the income structure. This is being found if one looks at the expenditure side. Households in low income countries devote more important shares of their income on food consumption than households in developed countries. This is what has been formulated in the famous *Engel's Law*. Hence, these households are particularly vulnerable for food price changes as this volatility may put the purchasing power of kind and cash income at risk: Food prices that suddenly increase devaluate income at hand that had been planned for food consumption. In addition, very few households reach food self-sufficiency by their agricultural activity. Thus, it is suggested to modify the underlying index and to include measures of food price volatility in order to trigger indemnity payments. If the objective would be to increase formal insurance demand by increasing the predictive power of the underlying index, this would be the logical implication.

However, redefining indexes raises other concerns as local food prices are influenceable by local traders. Hence, future research should be concerned with the question, which level of measuring food prices is appropriate to reconcile the requirement of a non-influenceable index variable and a sufficiently high correlation with local food prices to predict purchasing power variations at the local level.

In order to make individuals participate in formal insurance schemes, this must be more beneficial compared to a situation where the individual conducts informal risk management. Products should therefore more appropriately target towards potential customers and be aware of the processes used to generate income. Redefining the index in the proposed way could be one potential solution to increase take-up for formal products.

5 General conclusions

The dissertation was concerned with the position of agricultural low income households in developing and emerging countries. It shed light on their role as *"hedge fund managers"* managing their risky portfolio of income generating activities, income threatening risks and the formal as well as informal management of these risks.

The chosen approach was straightforward. In a first step, drought and food price induced risks and their effect on different household level outcome variables have been quantified in a broad review of recently published articles. The quantification of drought risks has shown that welfare effects are substantial in magnitude. While drought events affect all types of agricultural households equally negative, the conclusions with respect to food price volatility were multilayered: While rural producers tend to profit from increasing food prices in particular due to second-round effects, poor urban net consumers with limited abilities to trade quality for quantity were the ones most negatively affected from variable food prices. More broadly speaking, poor households in urban and rural settings are usually on the losing side.

In the following, labor market related risk coping strategies have been reviewed. Labor markets are an effective instrument to raise further income in the aftermath of a shock event. However, it is important to note that the shock absorbing power of labor markets depends on their structure, in particular on their degree of relatedness to agriculture as well as on the magnitude of labor demand and supply elasticities. While labor markets provide a certain degree of coping power, the time lag of wage adaptations might be substantial and thus reduce the coping power. Other risk coping strategies may have adverse consequences for low income households such as a reduced rate of human capital accumulation or losses in specialization.

The third chapter of the dissertation analyzed informal risk management in the form of labor time allocation where households under study split up their labor time potential over different income generating activities. The data set allowed distinguishing between farming and labor market activities. However, the labor market activities were not distinguished between agricultural and non-agricultural labor. The main result is that production and price risks affect the decision to allocate the labor time allocation. Farm production risk, modelled by the standard deviation of long-run rainfalls stimulated the time allocation towards the own farm. Thus, whenever the production risk increases marginally, households allocate more time resources towards own farm work. This counterintuitive result has been explained by the structure of labor markets: Labor markets are predominantly related to agriculture. Whenever production risks are more pronounced, labor demand falls. Hence, the only option for households to employ labor resources is to work on the own farm. The evidence with respect to food price variability was in line with theoretical considerations: An increase in the purchasing power risk induced by variable food prices decreased the amount of time allocated towards labor markets. This result was confirmed by subgroup analysis leaving out rice and wheat farmers from the regression and controlling for home consumption of produced agricultural goods. This risk-induced reallocation of resources leads to a concentration of time resources in agriculture. However, agricultural productivity is threatened by rainfall variability such that food price volatility emphasizes rainfall induced production risks and prevents households from diversifying their income portfolio.

Chapter 4 of the dissertation was concerned with analyzing formal insurance demand by agricultural low income households and its relation with informal risk management activities. It was argued that households apply informal risk management by splitting up their labor time potential across farming, agricultural and non-agricultural labor. The resulting degree of informal protection affects the incentive to buy formal drought insurance as a household's income profile is then individually susceptible towards rainfall variability. For instance, those households who earn relatively high income shares from non-agricultural labor should have fewer incentives to buy drought insurance as rainfall variability threatens a smaller share of their income portfolio. The analyzed household data set provided evidence in favor of that hypothesis and found a negative relation between the share of non-agricultural wages and the probability of insurance demand.

It has been shown that it is of decisive importance to reconcile informal risk management strategies and insurance product design. Informal risk management has evolved over decades and formal insurance products have to fill the gap that was left over by the inefficiencies of informal risk management. If the objective would be to increase formal insurance demand, it has been argued that the indemnity determination mechanism of index-based drought insurance products needs to be modified to capture the income risk composition after informal risk management has been conducted.

Formal insurance products have the advantage to give policyholders a right to claim compensation and not to beg for help in case of hardship. In addition, formalizing insurance has the potential to make crisis intervention more effective and to transfer more rights to the desperates. Moreover, formal insurance provides incentives for prevention and offers other positive side effects such as establishing precise data collection and management systems as well as developing technology and financial systems. What is essential is that formal insurance products have to be adapted to the specific needs of potential future customers. Conversations with practitioners revealed interesting insights: In particular, practitioners emphasized the importance of raising the take-up rate. A representative of a development agency told me about his positive and take-up increasing experiences by delaying premium payments and collecting them at the end of the agricultural cycle. By doing so, he claimed to raise take-up rates to a level of *"75 %, and the remaining 25 % are a group you will never reach."* Even though this seems to be an overwhelming success in terms of generating up take, this strategy is double-edged: Selling a product of which one is not sure whether it traces the income risk of the insured appropriately and achieving a high take-up by relaxing the budget constraints may create disappointment and anger among the insured when the income volatility prediction of the index turns out to be inappropriate. If an insurance product is supposed to be sold sustainably, one should focus on a high take-up and contract renewal rate instead of focusing on the take-up rate exclusively. A high contract renewal rate is achieved by an appropriate product design. Thus, one major aspect of this dissertation was to plead in favor of a consistent risk assessment and a careful product design before the formal insurance product is sold. It is a logical necessity to design the product such that it fits to the income risk structure in the best possible way. In a next step, one can add all kinds of marketing instruments such as training and education sessions, delayed premium payments and other subsidies to push the product into markets.

This dissertation has shown that informal risk management is the suitable instrument to cope with less severe risks and should therefore be anticipated in the product design of formal insurance products. The decision space of agricultural household management is not polarized between informal risk management on the one extreme and formal insurance demand on the other extreme. Instead of choosing one of the corner solutions, layering income risks and addressing them with appropriately designed risk transfer instruments as well as reconciling them with informal risk management strategies would be a much more effective and promising approach to reduce the burden of low-income hedge-fund managers.

Appendix A

	(I) *farm_days* Pooled-OLS	(Ia) *farm_days* Pooled-OLS
age	3.842***	4.447***
	(6.59)	(7.04)
age2	-0.0414***	-0.0473***
	(-6.02)	(-6.07)
yrs_edu	-2.946***	-2.657***
	(-5.20)	(-5.23)
hh_size	-0.494	-1.023
	(-0.75)	(-1.53)
farm_size	1.044*	1.299**
	(2.05)	(2.24)
cap_input	0.000250***	0.000141
	(3.08)	(1.70)
irriare	22.23***	18.26***
	(4.71)	(4.06)
stdrain	13.49***	14.69***
	(18.13)	(21.44)
stdrice	0.0511***	0.0750***
	(3.60)	(6.29)
stdwheat	0.204***	0.193***
	(7.17)	(7.48)
consumption	0.00000163	0.00000122
	(0.75)	(0.69)
degab	37.82***	36.53***
	(6.17)	(6.06)
soilfert	-0.343	2.277
	(-0.04)	(0.31)
male	41.59***	42.13***
	(3.86)	(3.65)
married	16.37***	16.19***
	(4.64)	(4.70)
mrkt_dist	2.203***	0.105
	(4.31)	(0.21)
migration	-40.14	-7.202
	(-0.85)	(-0.15)
Observations	8570	7829
R^2	0.334	0.341

t- statistics in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$ The dependent variable is the number of farm days per calendar year. All regressions, except regression (IIa), contain village and year dummies. The constant has not been reported in the table.

Table A-1: Complete regression results I

	(II) *lmpart* Probit	(IIa) *lmpart* AME	(III) *work_days* Pooled-OLS
age	0.155***	0.0425***	8.919***
	(21.57)	(20.76)	(5.80)
age2	-0.00185***	-0.000507***	-0.102***
	(-24.13)	(-23.48)	(-6.36)
yrs_edu	-0.0126	-0.00344	4.775***
	(-1.19)	(-1.20)	(4.46)
hh_size	0.0115	0.00315	0.607
	(1.09)	(1.08)	(0.41)
farm_size	-0.0521***	-0.0143***	-2.270***
	(-5.51)	(-5.51)	(-3.05)
cap_input	-0.000000583	-0.000000160	-0.0000425
	(-0.37)	(-0.37)	(-0.37)
irriare	-0.396***	-0.108***	-11.36*
	(-4.89)	(-4.92)	(-1.91)
stdrain	-0.0496	-0.0136	-16.44***
	(-0.83)	(-0.84)	(-12.34)
stdrice	-0.00113***	-0.000308***	0.0361**
	(-2.87)	(-2.96)	(2.38)
stdwheat	-0.000153	-0.0000419	-0.100**
	(-0.12)	(-0.12)	(-2.50)
consumption	2.48e-08*	6.79e-09*	7.70e-08
	(1.89)	(1.87)	(0.03)
degab	0.641***	0.175***	11.70
	(5.81)	(6.50)	(0.79)
soilfert	0.0430	0.0118	1.857
	(0.25)	(0.25)	(0.20)
male	0.608***	0.167***	25.13***
	(4.64)	(5.01)	(4.36)
married	-0.168	-0.0461	-22.29***
	(-1.29)	(-1.28)	(-2.97)
mrkt_dist	-0.0803***	-0.0220***	-0.370
	(-2.67)	(-2.75)	(-0.33)
Observations	8054	8054	3816
R^2			0.193

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is a dummy of labor market participation in column 1 and the number of labor market days for those who reported an active labor market participation in the last column. All regressions, except regression (IIa), contain village and year dummies. The constant has not been reported in the table.

Table A-2: Complete regression results II

Appendix B

	(I) *ins_lev* Probit	(Ia) *ins_lev* AME	(II) *ins_lev* Probit	(IIa) *ins_lev* AME
exp_rain	-0.0491	-0.0158	-0.0407	-0.0131
	(-0.50)	(-0.50)	(-0.41)	(-0.41)
d_highedu	0.121	0.0389	0.139	0.0446
	(0.91)	(0.91)	(1.07)	(1.07)
age_head	0.00495	0.00159	0.00506	0.00162
	(1.00)	(1.00)	(1.02)	(1.01)
muslim	-0.172	-0.0553	-0.131	-0.0419
	(-0.81)	(-0.82)	(-0.65)	(-0.65)
riskav	-0.423**	-0.136**	-0.437**	-0.140**
	(-2.31)	(-2.33)	(-2.36)	(-2.37)
inc_total	-0.000000239	-7.70e-08	-0.000000139	-4.44e-08
	(-0.51)	(-0.51)	(-0.28)	(-0.28)
hhsize	0.00103	0.000330	0.00146	0.000469
	(0.05)	(0.05)	(0.08)	(0.08)
sexhead	0.0358	0.0115	0.0293	0.00941
	(0.19)	(0.19)	(0.16)	(0.16)
ins_other	0.418***	0.134***	0.441***	0.141***
	(2.83)	(2.90)	(3.04)	(3.12)
dfrg	0.0110	0.00352	0.0135	0.00432
	(0.42)	(0.42)	(0.52)	(0.53)
wsa	-0.208	-0.0668		
	(-1.15)	(-1.14)		
mean_payouts	0.542*	0.174**	0.542*	0.174**
	(1.91)	(1.99)	(1.96)	(2.04)
lculirrpct	-0.0306	-0.00985	-0.0218	-0.00698
	(-0.30)	(-0.30)	(-0.21)	(-0.21)
group_add	0.0499	0.0160	0.0498	0.0160
	(0.53)	(0.53)	(0.53)	(0.53)
wsna			-0.383**	-0.123**
			(-2.05)	(-2.04)
Observations	885	885	885	885

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in all regressions is the dummy variable *ins_lev* taking on a value of 1 if the respondent had at least a policy for one Monsson phase. All regressions, except regression (Ia) and (IIa) contain village dummies.

Table B-1: Complete regression results (Schooling level specification)

	(III) *ins_lev* Probit	(IIIa) *ins_lev* AME
exp_rain	-0.0335	-0.0107
	(-0.34)	(-0.34)
d_highedu	0.135	0.0433
	(1.03)	(1.03)
age_head	0.00488	0.00156
	(0.99)	(0.99)
muslim	-0.121	-0.0386
	(-0.56)	(-0.56)
riskav	-0.458**	-0.147**
	(-2.39)	(-2.40)
inc_total	1.37e-08	4.38e-09
	(0.03)	(0.03)
hhsize	-0.00192	-0.000615
	(-0.10)	(-0.10)
sexhead	0.0221	0.00706
	(0.12)	(0.12)
ins_other	0.469***	0.150***
	(3.30)	(3.40)
dfrg	0.0137	0.00437
	(0.56)	(0.56)
mean_payouts	0.555**	0.178**
	(2.09)	(2.18)
lcultirrpct	-0.0217	-0.00696
	(-0.21)	(-0.21)
group_add	0.0500	0.0160
	(0.52)	(0.52)
wsa_pc	-0.0000350**	-0.0000112**
	(-2.21)	(-2.20)
Observations	893	893

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in all regressions is the dummy variable *ins_lev* taking on a value of 1 if the respondent had at least a policy for one Monsson phase. Regression (III) contains village dummies which have not been reported.

Table B-2: Complete regression results (Schooling level specification)

	(IV) *ins_lev* Probit	(IVa) *ins_lev* AME	(V) *ins_lev* Probit	(Va) *ins_lev* AME
exp_rain	-0.0260	-0.00831	-0.0176	-0.00561
	(-0.26)	(-0.26)	(-0.18)	(-0.18)
ins_skill	0.166***	0.0531***	0.168***	0.0536***
	(2.63)	(2.63)	(2.63)	(2.62)
age_head	0.00475	0.00152	0.00474	0.00151
	(0.89)	(0.89)	(0.88)	(0.88)
muslim	-0.165	-0.0528	-0.120	-0.0384
	(-0.76)	(-0.77)	(-0.59)	(-0.59)
riskav	-0.366**	-0.117**	-0.382**	-0.122**
	(-1.98)	(-1.99)	(-2.04)	(-2.05)
inc_total	-0.000000247	-7.91e-08	-0.000000139	-4.43e-08
	(-0.53)	(-0.53)	(-0.28)	(-0.28)
hhsize	-0.000427	-0.000137	-0.000187	-0.0000596
	(-0.02)	(-0.02)	(-0.01)	(-0.01)
sexhead	0.0931	0.0298	0.0912	0.0291
	(0.50)	(0.51)	(0.50)	(0.50)
ins_other	0.418***	0.134***	0.442***	0.141***
	(2.77)	(2.86)	(2.99)	(3.09)
dfrg	0.00337	0.00108	0.00550	0.00176
	(0.13)	(0.13)	(0.21)	(0.21)
wsa	-0.215	-0.0688		
	(-1.21)	(-1.20)		
mean_payouts	0.312	0.0996	0.306	0.0978
	(1.07)	(1.09)	(1.06)	(1.09)
lcultirrpct	-0.0449	-0.0144	-0.0334	-0.0106
	(-0.41)	(-0.42)	(-0.30)	(-0.30)
group_add	0.0652	0.0208	0.0657	0.0210
	(0.69)	(0.69)	(0.70)	(0.70)
wsna			-0.380**	-0.121**
			(-2.03)	(-2.01)
Observations	885	885	885	885

t-statistics in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$. The dependent variable in all regressions is the dummy variable *ins_lev* taking on a value of 1 if the respondent had at least a policy for one Monsson phase. Regressions (IV) and (V) contain village dummies which have not been reported.

Table B-3: Complete regression results (Financial literacy specification)

	(VI) *ins_lev* Probit	(VIa) *ins_lev* AME
exp_rain	-0.00876	-0.00279
	(-0.09)	(-0.09)
ins_skill	0.171***	0.0545***
	(2.68)	(2.67)
age_head	0.00454	0.00145
	(0.86)	(0.86)
muslim	-0.112	-0.0357
	(-0.51)	(-0.51)
riskav	-0.401**	-0.128**
	(-2.08)	(-2.08)
inc_total	6.09e-09	1.94e-09
	(0.01)	(0.01)
hhsize	-0.00312	-0.000995
	(-0.16)	(-0.16)
sexhead	0.0823	0.0262
	(0.46)	(0.46)
ins_other	0.471***	0.150***
	(3.25)	(3.37)
dfrg	0.00578	0.00184
	(0.23)	(0.24)
mean_payouts	0.317	0.101
	(1.14)	(1.17)
lcultirrpct	-0.0320	-0.0102
	(-0.28)	(-0.28)
group_add	0.0669	0.0213
	(0.70)	(0.70)
wna_pc	-0.0000339**	-0.0000108**
	(-2.16)	(-2.14)
Observations	893	893

t-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in all regressions is the dummy variable *ins_lev* taking on a value of 1 if the respondent had at least a policy for one Monsson phase. Regression (VI) contains village dummies which have not been reported.

Table B-4: Complete regression results (Financial literacy specification)

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