Impact of Flood Meso-Insurance on Agricultural Productivity: Evidence From Bangladesh

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Abstract

Between 2012 and 2015, Oxfam Bangladesh launched a unique flood meso-insurance program across three districts of Bangladesh. Comparing differences in quantities harvested over time between the covered districts and a few comparable non-covered districts, our results suggest that there is a substantial increase in quantities harvested in the areas where the flood insurance was put into place. We were able to estimate the average increase in quantities harvested of approximately 4% after the flood insurance program was implemented in the covered districts.

1 Introduction

Almost three quarters of the world population living on less than one US dollar per day depend on agriculture for their livelihood (World Bank, 2005). Therefore, it is extremely important to look for ways to increase farmers' productivity and income while reducing poverty. It becomes a more critical matter for farmers in less developed economies, who face significant barriers in access to credit, insurance and other financial products taken for granted in developed countries. In the aforementioned case, the farmers may opt for less productive and lucrative activities to avoid the various risks they are facing in the absence of adequate financial products such as insurance coverage in the case of natural disasters. Hence, as Barrett et al. (2007) pointed out, uninsured climate risk can keep low-income households in poverty traps. In agriculturally dependent economies, weather is a significant factor for economic well-being. Particularly in areas of rain-fed agriculture, weather variations are a major determinant of agricultural production. While variations are expected, natural disasters such as torrential rain, flooding, and prolonged drought can devastate a rural economy by damaging the major source of household, regional, or national income. Where there are no mechanisms in place to protect against large losses from extreme weather events, income and economic activities are likely to be depressed. Mismanaged weather risk can contribute to poverty and inhibit development.

Unfortunately, though there is a large literature covering the benefits of micro-finance as a medium for poverty reduction, the literature on the effects of micro-insurance as a poverty reduction tool is limited. Clarke et al. (2006) noted that the studies on the impact of micro-insurance were rare, due in part to skepticism about the ability to create an effective insurance scheme that would help the poor while being profitable for private insurers. However, knowing that more than 30 years ago the idea of a sustainable and profitable micro-finance industry was rejected by the majority of researchers and practitioners remains a great source of encouragement. In other words, the fact that the micro-finance system faces similar issues of high transactions costs, moral hazard, adverse selection, limited cash flows, low education levels of clients, and weak enforcement mechanisms gives us a reason to not completely close the case of a viable flood insurance system that would help the rural farmers to get out of poverty.

Studying the causal effect of insurance on agricultural production using observational data is a challenging task because of the problem of unobserved heterogeneity. Individuals with certain traits may self select into some specific insurance scheme, and these unobserved traits may also affect the choice of production technology, effort level and thus the output level. For instance, more risk averse farmers may prefer insurance and at the same time devote more efforts to move to less disaster-prone areas. The presence of self-selection may cause a spurious correlation between insurance coverage and agricultural output. Therefore, using a Randomized Control Trial (RCT) identification strategy is usually the best method to control for heterogeneity, but given the cost and the resources that RCT requires, we decided to focus on a natural experiment observed between 2011 and 2015 in Bangladesh. Our paper will study an innovative flood meso-insurance program designed to mitigate income risk among small agricultural producers in Bangladesh. Our sample of farmers is living in some of the neighboring districts of the Surma-Meghna river system where flood and rainfall are the major sources of production and income risk. In this context, we will study the effects on behavior of a flood insurance policy, which partially insures against a flood damages by providing a payout contingent on high measured local rainfall. In order to mitigate the heterogeneity bias we followed a very similar approach to Vickerie et al (2013), they chose to study the impact of a rainfall index insurance to remove the self-selection problem. In our study, the index meso-insurance that we are analyzing will guarantee the elimination of adverse selection bias and the fix payout amount will significantly reduce the moral hazard bias.

In Section 1, we provide a literature review on the impact of weather insurance on agricultural behaviors. Section 2 gives the motivation for a flood insurance program in Bangladesh and details the data sets and describe our natural experiment. Section 3 presents the methodology and the identification strategy. Section 4 examines the descriptive statistics and the model specification. Section 5 presents the results for quantity harvested. The last section is the conclusion.

2 Literature Review

There are various types of insurance that can help to efficiently mitigate poverty. Among the most well established in the literature, we can mention life and health insurance. However, life and health insurance will only protect against the individual vulnerability of the policy holder . If we want to improve the agricultural systems, there needs to be other insurance products provided and available to farmers such as insurance in the case of a natural disaster. If the introduction of an index-based insurance (e.g., area-based yield insurance or insurance based on rain fall or other weather indices) in a community can significantly decrease weather crisis impact on farmers, it is worth considering the availability of such insurance as a poverty measure in rural areas. For our study, we chose such insurance product because we would like to evaluate a policy that can impact the farmers' production decisions. One advantage of an index-based insurance is that it has the virtue of being moral hazard proof in the sense that it preserves effort incentives for producers as no individual farmer can influence the probability of an insurance payout. It eliminates adverse selection problems, because the expected insurance scheme is based on factors that are exogenous to the farmers. Surprisingly, the development of index-insurance pilot projects has been widespread but little is known about their impact.

Moreover, many developing countries have started to develop and market formal insurance products to shield farmers from risks, even though take-up is surprisingly low despite heavy government subsidies. There is a growing literature studying means to improve insurance demand (Gaurav et al. (2011), Cai and Wei (2012), Cai and Song (2012), Bryan (2010)), but rigorous evaluations of the impacts of insurance provision are quite rare. One perfect illustration being Gaurav et al. (2011) who conducted a randomized experiment which provided free rainfall insurance for selected farmers in India, but they were more focused on the impact of financial literacy on the index-insurance demand. In the following paragraphs we will review the main findings of theoretical, empirical and simulation studies on the causal effect of index-insurance on farmers' behaviors.

2.1 Theoretical Models

To the best of our knowledge, three main theoretical frameworks have been developed in the literature. Firstly, Carriquiry and Osgood (2012) formalize the interaction between the choice of both insurance and input purchases in the presence of a skillful forecast also known as index-insurance. They show that in theory, the implementation of an index insurance in the absence of moral hazard will induce farmers to take on more risk and to increase their level of input use when insured. Secondly, Chambers and Quiggin (2002) similarly examined the relationship between index insurance and input usage and found that the introduction of an index insurance such as area-yield or rainfall insurance will increase systematic risk. Thirdly, Mahul (2001) concluded that the purchase of actuarially fair weather insurance induces the risk-averse and prudent producer to increase his use in risk-increasing input and decrease his use in risk-decreasing input.

2.2 Empirical Studies

A few number of papers attempted to study the direct effect of index-insurance on the farmers' behaviors. Karlan et al. (2014) provided free insurance to a full population as part of a multiarm Randomized Control Trial

(RCT) in order to observe the effects of rainfall insurance on investments and they find that the introduction of rainfall insurance induced strong responses of agricultural investments. Giné and Yang (2009) randomly selected maize and groundnut farmers in Malawi where they bundled insurance with loans for a group of farmers and offered loans without insurance to another group of farmers and their results showed a negative effect of insurance on borrowing. Cole et al. (2013) employ a field experiment approach that builds on a series of field experiments and surveys that they have conducted since 2004 in Andhra Pradesh, India (Giné, Townsend and Vickery (2008) and Cole et al. (2013)). They found that the impact of insurance provision on the entire agricultural investment is negligible, but it still causes significant shifts in the composition of the investment(fertilizer, seeds, land). Hill and Viceisza (2010) conducts a framed field experiment in rural Ethiopia and insurance was found to have some positive effect on fertilizer purchases. Liu (2013) randomizes a small sample of farmers in China and he examines the impact of insurance on the total number of piglets purchased and as already predicted by other experiments, he observes that without insurance households under-invest in remunerative but risky activities. Janzen and Carter (2013) report the impact of the index-based livestock insurance (IBLI) pilot project in Marsabit district of northern Kenya and their main result is that insured farmers are less likely to sell their livestock and more likely to maintain food security in their household after a climate shock (such as drought) occurs.Finally, Gaurav et al. (2011) study 15 rain-fed villages across three coastal districts in India, their focus is on the influence of financial education as a mean to increase rainfall insurance purchase and they find that farmers educated in financial literacy and insurance are significantly more likely to adopt rainfall insurance.

2.3 Simulation Studies

A simulation study conducted by Rosenzweig and Wolpin (1993) shows that availability of index-insurance has low impact on farmers' well-being. This is due to farmers' aversion to risk combined with borrowing constraints and low incomes. A more recent simulation study came from Carter et al. (2007) where they study the effect of index-insurance on credit supply and farmers' loan repayment and welfare in Peru, they specifically use a shorter panel of data from 2002 to 2004 of 176 rice producers in the same valley to estimate the parameters of the individual yield distributions. Nicola (2015) uses calibrated parameters to determine the impact of insurance on farmers' welfare and she finds that insurance welfare contributes to significant welfare gains even in the context of potentially low take-ups. Mobarak and Rosenzweig (2012) conducted a controlled experiment to sell an index insurance product to households drawn randomly in Indian villages because they wanted to study how informal insurance affects the demand for a formal insurance product and farmers' behaviors. They find that formal insurance is imperfect due to a mismatch of index-insurance payouts, however, the existence of an informal risk sharing system, enhances the benefits of a formal index-insurance product and triggers an increase in farmers' risk taking.

2.4 Our Contribution

The paper has the purpose of complementing the growing literature mentioned above. Although we are also interested in studying the impact of an index-insurance program on agricultural production in developing countries, our study slightly differs from the previous ones in two main aspects. Firstly, to the best of our knowledge there has never been some research on the causal effect of index-based insurance on agricultural production in Bangladesh, the closest study being in the neighboring countries India and Pakistan. Secondly, the identification strategy that was widely used in the most prominent studies was the Randomized Control Trial (RCT) method and the researchers were interested in evaluating the impact at the village-level. Whereas, we exploit a natural experiment that randomly selected the first three districts of a pilot project implementing for the very first time a meso-insurance program, where communities rather than individual households can enroll into the flood insurance program. Therefore, we are expecting our findings to be a little more general.

3 Motivation for a Flood Insurance Program

According to the theory, poor farmers in rural areas are likely to organize an informal insurance system in the absence of formal insurance services. There is a wide literature documenting the mechanisms and assessing the effectiveness of informal risk-sharing schemes among rural populations in poor countries, and especially in Bangladesh and India (Mazzocco and Saini (2017); Townsend (1994); Ravallion and Dearden (1988); Rosenzweig (1988); Rosenzweig and Stark (1989)).

However, these studies generally find that risk-sharing is incomplete, which in turn leads exposed farmers to choose low risk and lower-yield production methods, asset portfolios, and crops, instead of riskier but more profitable alternatives (Binswanger et al. (1993); Carter and Barrett (2006)). Various frictions such as information asymmetries, contract enforcement costs and fraud limit the ability of formal credit and insurance markets to mitigate risk (Rothschild and Stiglitz (1978); Finkelstein and McGarry (2006)). In recent years, weather index-based insurance has sparked much interest among development researchers and practitioners as a prominent alternative that addresses some of these concerns (IFAD 2010; World Bank 2010).

Bangladesh is one of the most disaster-prone nations in the world. Every year, about 10 million Bangladeshi citizens are impacted by one or more natural hazards. In the past, the government of Bangladesh had a traditional reactive approach to addressing natural disasters that focused on relief and rehabilitation activities. This changed in 1989, when a Flood Action Plan (FAP) was launched to manage the risk induced by flood-related damages. However, as Custers (1993) would descibe it, the main objectives of the plan were not achieved and although several infrastructure sites were built (e.g. cyclone shelters and the Centre for Environmental and Geographic Information Services (CEGIS) was established), the people remained as vulnerable to flood disasters as they were before the FAP had been initiated. Demographic and economic growth in the following 20 years have increased Bangladesh's exposure to damaging floods. Hence, in 2009 there was a need for a new disaster management plan for the then newly elected government, and in 2016 the National Development Plan was officially launched. Consequently, there has been a gap in terms of flood policy between 2009 and 2016 in Bangladesh. Given the fact that Bangladesh could not afford a decline in agricultural productivity levels due to the fast population growth, we aimed to study the impact of one of the many flood insurance projects implemented in Bangladesh between 2009 and 2016, and to evaluate whether or not it helped increase the agricultural productivity in the treatment districts in comparison to the control districts.

3.1 Data Sources

One of the main challenges faced at the early stage of our study was to find available data related to flood insurance provision in Bangladesh at the household-level. It would not have been easy to analyze the impact of a micro-insurance flood program without the specific information about insured individual households. Fortunately, we discovered a program that allowed us to get around the issue mentioned above by studying a meso-insurance instead of a micro-insurance scheme. The main difference between meso-insurance and micro-insurance is that individual households can subscribe to a specific micro-insurance product to cover their assets in the event of natural disaster, whereas a meso-insurance program insures a large group of individual households such as a community ,a district or a province. In fact, the flood meso-insurance scheme implemented by Oxfam between 2013 and 2014 was not the typical flood micro-insurance offered to individual households. It was rather offered to large communities or to districts, which relaxed the constraint of identifying the individual households subscribed to the insurance policy within the community or the district. Since we could guarantee that as long as a geographical or administrative area was covered by the program, any household within that area was insured against flood disasters.

The data used for this paper come from the Bangladesh Integrated Household Survey (BIHS), which is the most comprehensive and nationally representative rural household panel survey in the country to date. The BIHS 2011-2012 and 2015 panel dataset is funded by the U.S. Agency for International Development (USAID), designed by the Bangladesh Policy Research and Strategy Support Program (PRSSP) implemented by IFPRI, and administered by Data Analysis and Technical Assistance (DATA). The first round survey took place between 2011 and 2012, while the second round survey took place in 2015. We chose to use the BIHS because it is the only such survey to collect data on plot-level agricultural production and practices. The database also provides information on survey year, location, individual household members information, dietary intake of individual household members, anthropomorphic measurements (height and weight) of all household members (not just women of child-bearing age and children under-five) and data to measure women's empowerment via the women's empowerment in agriculture index (WEAI).

The BIHS dataset is representative at various levels: across all of rural Bangladesh; throughout all seven of the country's administrative divisions Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet; and at the USAID-supported "Feed the Future" zone of influence in the southern Bangladesh. In the first round, the BIHS collected data across 6,500 households. The attrition between 2011-2012 and 2015 was exceptionally low, at just 1.26 percent per year. Additionally, the BIHS deployed two survey instruments, first, gender-disaggregated household questionnaires, designed to collect individual- and household-level information from both the primary male and female respondents, who were interviewed separately; and second, a community questionnaire to provide information on area-specific contextual factors.

3.2 Oxfam Flood Meso-Insurance Scheme

The flood insurance policy offered in this study is a type of index insurance to which NGO's and the government can subscribe in every district. In other words, the farmers do not directly subscribe to the policy. The pilot project was conducted from June 2012 to March 2014 and was initially launched in 10 villages (Phanchasona, Mollikpara, Muradpur, Khasboroshimul, Fulhara, Chakbayra, Choto Chouhali, Boro Chouhali, Aknadiqhi, Village Fulbari) during the flood season 2013. The development of such an index-based meso-insurance required available historical and real-time weather data and the prediction model was the Flood Hazard Model used by Swiss Re for Index Preparation, Product Structuring Pricing and claim settlement. In August and September 2014 four villages that were covered by the insurance suffered flood damages and the first payouts took place for all the households affected and they received a total compensation of 13,800,000 Taka (approximately 163,307.96 US Dollar).The insurance plan was designed so that if water levels cross a certain locally-determined threshold and stay for 11 days, a household will get 2,800 taka (36 USD); if floods stay for 21 days, the household receives 4,400 taka (56 USD); and at 26 days, 8,000 taka (103 USD). Therefore, in 2014 each household received the equivalent of 36 USD and given that the Overseas Development Institute estimates the average daily wage of rural farmers at 2.78 USD in 2010 in Bangladesh, the payout was quite equivalent to their earnings without flood. According to the Integrated Regional Information Networks (IRIN), a former project of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) that became an independent in January 2015 the project was expanded across three districts Sirajgonj, Gaibanda and Borgona.

As we mentioned earlier an index-insurance is rarely subject to self-selection bias. In addition, an index-based flood insurance scheme involves lower administrative costs since no claim verification process is required. However, one of the major setbacks could be that flood insurance products only cover flood-related losses with payouts based on a certain water level threshold (checked by an agent after the flood), a threshold that is difficult to set due to the high volatility of rainfall levels in Bangladesh. Hence, there is a high risk that the payouts become too expensive for such a project to be viable and sustainable.

4 Identification Strategy

In this section, we first provide evidence that despite the attrition that causes an unbalanced panel data, we were able to find estimates that are consistent. We then describe the main specification and the controls.

4.1 Identification Assumption

In our model we consider that the attrition rate in our data is sufficiently low to assume that there is no attrition bias and that the panel data is representative. The various estimators presented in this section are somewhat easily implemented using a method that helps us to analyze an unbalanced panel data with random attrition, almost as a balanced panel data with with one equation. We also consider the heterogeneity (the differences across the households being studied) issue caused by the existence of unobserved variables influencing the model. In order to account for the heterogeneity we have chosen to use a random effect model rather than a fixed effect model.

The key identification assumption is that we treat any unobserved individual heterogeneity as being distributed independently of the regressors. This assumption allows us to obtain a consistent estimation of all parameters, including coefficients of time invariant regressors. The consistency of our model estimation resides on the absence of fixed effects in the model. Since the coverage of a district or community was independent of individual characteristics but mainly dependent on the proximity to the Surma-Meghra river, it is safe to assume that the individual fixed effects do not affect the impact of a meso-insurance on the productivity.

5 Descriptive Statistics

For the purpose of our study, we compared the three districts where the flood insurance was implemented, namely Sirajgonj, Gaibanda and Bogra, to three districts that were considered similar in terms of geographical position (for example the proximity from the Surma-Meghra river) as well as other weather-related criteria. The three districts that we chose were Jamalpur(similar to Sirajgonj), Bogra(similar to Gaibanda), and Patuakhali (similar to Borgona). We will provide some statistics for each pair of districts in the year 2011, before the policy was implemented. Although it might have been more informative to compare the same districts over a period of time longer than one year, our current dataset did not include information for the year 2015. We summarized the three comparisons in table 1, table 2 and table 3 of our Appendix section.

5.1 Model Specification

Following the work of Laird and Ware (1982) who develop a model where they assume that the unobserved individual effects are random variables that are distributed independently of the regressors. We also incorporate a time dummy variable $AFTER$ that takes the value zero if the survey was conducted in 2011 and one if the survey was conducted in 2015. Our variable of interest is the variable $INSURANCE$ which represents the three districts covered by the flood insurance in comparison with three similar districts that were not covered; The variable $INSURANCE$ is a dummy variable that takes the value one if a district is covered by the flood insurance and zero if the comparative district is not covered by the insurance. Finally, we also added an interaction term between INSURANCE and AFTER captures the effect of the insurance in the covered districts compared to those not covered by the policy. We can formalize our model as it follows:

$$Y_{itd} = \alpha_i + \gamma AFTER_t + \theta INSURANCE_d + \psi INSURANCE_d AFTER_t + X'_{ct}\beta + \varepsilon_{it} \quad (1)$$

$$\alpha_i \sim [\alpha, \sigma_\alpha^2] \quad (2)$$

$$\varepsilon_{it} \sim [0, \sigma_\varepsilon^2] \quad (3)$$

where y is the natural logarithm of the quantity harvested per household, i in the district. X_{ct} is a vector of individual characteristics (dummies of marital status, religion, educational level and household size). The model is straightforward and if significant, the results will allow us to estimate the impact of the introduction of the flood insurance policy on the quantity harvested at the district level.

6 Results

6.1 Empirical discussion

In Table 7 we estimate the impact of insurance on the natural logarithm of the quantities harvested per household after the policy was implemented in the three treatment districts. We ran our regression with the intent to exclude individual-specific fixed effects from our estimation. We include a few dummy to the model variables namely the household head's marital status, religion and education level.

As predicted by the theory, our preliminary results show that the introduction of the flood insurance program has a positive and significant impact on the quantities harvested after the flood insurance scheme was introduced in the three treatment districts. We also notice that our results are all significant at the 5% level for the interaction term. As one could expect, household size is also significant in our model. In addition to that, the results of table 7 seem to show that religion is not neutral when it comes to agricultural productivity, but this might be the result of missing regressors in our model. Furthermore, the gender of the household head and his or her level of education affect the productivity of the farmers and it does not come with a surprise that a farmer with a bachelors degree will significantly improve his or her productivity compared to household heads with lower levels of education. Finally, marital status does not have any significant impact on quantities harvested after the flood insurance program was implemented.

We then decided to run a robust regression following the general framework for heteroskedasticity-robust tests in regression directions of Davidson et al.

(1985). Our findings are summarized in the Table 8 of our Appendix. What we find is that the results are consistent with the previous regression except that the coefficient of the farmers who earned a higher secondary certificate is no longer significant. While having a bachelors with honors and attending preschool are significant at the 1% level. As for the other coefficients, the significant and insignificant coefficients remained the same between the two tables. Therefore, we can safely anticipate that after flood insurance is provided in an area, individual-specific marital status will not affect the agricultural productivity, and that the farmers who completed at least class 3 are likely to be more productive. While, the farmers who completed class 9 or those who earned a bachelors degree would be even more productive. Most importantly, our two tables show that beyond the individual characteristics of each farmers, the introduction of insurance between 2011 and 2015 contributed to an increase in quantities harvested in the three districts covered by flood insurance in comparison with the three districts that were not covered.

6.2 Theoretical discussion

Following the model developed by De Nicola (2015), we propose a theoretical weather insurance model with the assumption that each farmer will be covered by ι units of insurance which each pays $(1-\eta)$ to offset any bad weather shocks. The optimization problem can be expressed as:

$$V(\omega, \varepsilon) = max_{k\geq 0} u(\omega - k) + \beta \mathrm{E} V[A\varepsilon_i k^\alpha a^{1-\alpha}\eta + \iota(1-\eta) - \iota\rho, \varepsilon_i'] \tag{4}$$

Where ρ is the insurance premium and ε_i represents weather shocks. β is the next period discount factor between 0 and $1.\omega$ is the farmer's wage.k

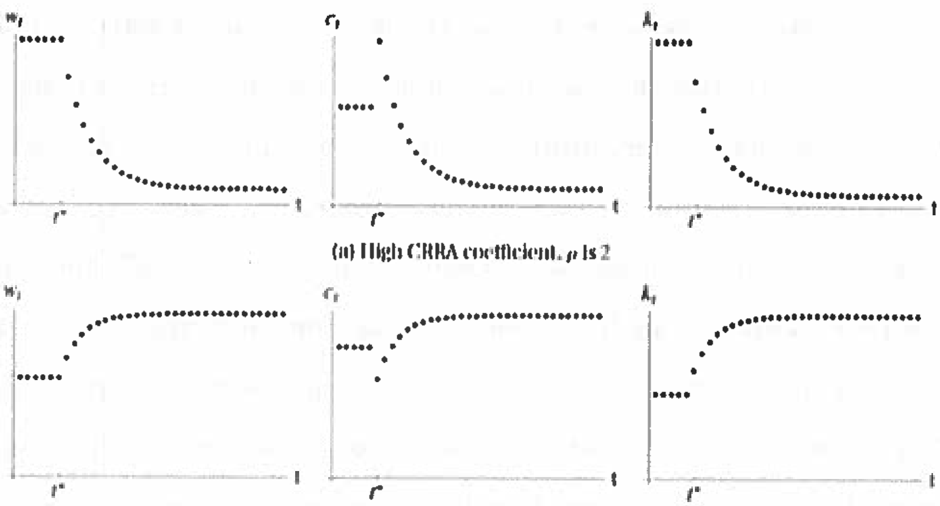
is a constant representing the cost of insurance and $A\varepsilon_i k^{\alpha} a^{1-\alpha}\eta$ is a Cobb-Douglas production functions with shocks and without any insurance with the parameter α between 0 and 1.

It is important to note that the insurance payout is perfectly correlated with the weather shocks and that we are neglecting the possible presence of basis risk. For the model to hold, we make another simplifying assumption. Indeed, we assume that the insurance premium is actuarially fair, so that

$$\rho = \int_{\bar{\imath}}^{1} (1-\eta) f(\eta) d\eta$$

The absence of basis risk and the actuarially fair premium, implies that farmers fully insure against weather shocks, hence the formulation of the insurance problem allows us to quantify the potential welfare gains that could be seized by designing effective insurance products. The farmers' optimization problem simply becomes the maximization of $V(\omega, \varepsilon)$. This allows us to proceed to an estimation and quantitative analysis. Additionally, from the quantitative analysis we can draw a few theoretical implications. Interestingly enough, the introduction of weather insurance has an ambiguous impact on investment that can either increase or decrease, depending on the parameter values. On the one hand, weather shocks deter investment since they create uncertainty in the rate of return. But on the other hand, weather risk can stimulate investment through a precautionary motive as farmers over invest so as to have enough income even in the case of negative weather shocks. In our setting, the output after bad shock is proportional to the level of investment. Therefore, investment can either increase or decrease when insurance offsets weather risk. To clarify with an example, Figure 1 traces the evolution of consumption and investment following the introduction of weather insurance under two different calibrations for the CRRA coefficient, which has a key impact on the investment response. More specifically, we set $\alpha = 0.7$, $\sigma_\varepsilon = 0.05$, and $\beta = 0.76$, let ρ be either 0.9 or 2, and initialize the impulse response functions at the target level of wealth without insurance, which remains constant until insurance is introduced at time t*.

Figure 1: Farmer's Investment Simulation



(a) High CRRA coefficient, ρ is 2

(b) Low CRRA coefficient, ρ is 0.9

Depending on the magnitude of the CRRA coefficient, the provision of weather insurance may either increase or decrease investment. More risk-averse individuals react to the provision of weather insurance by reducing the amount of capital invested given the weakening of precautionary motives (Figure 1(a)). Consequently, consumption jumps upward initially and then declines over time as the level of investment and income falls. Conversely, less risk-averse agents immediately cut consumption to finance additional investment (Figure 1(b)). Their consumption then gradually increases and eventually levels off at a higher level than under the baseline regime since farmers achieve higher income due to the initial increase in invested capital.

7 Policy Implications and Limitations

The most difficult part of any weather insurance project is the uptake level, even if it alternates from successes to failures, the results have often been disappointing. For that reason, the few cases where index insurance has been implemented were either free or heavily subsidized, or offering insurance along with other benefits such as subsidized credit and heavy technical assistance. In extensively studied cases in Malawi (Giné and Yang (2009)) and India (Cole et al. (2013)), take up was only 20-30% with adopters hedging only a very small fraction of agricultural income. Take up among farmers not explicitly targeted was much lower in these programs. There are, however, recent exception, with Karlan et al. (2014) reporting a 40-50% take up at fair price plus a 50% loading in Ghana, and insurance inducing an increase in investment in cultivation. In this case, experiencing insurance payouts either oneself or through social networks was an important determinant of demand. In general, however, low uptake is still the norm and it requires a better design of the insurance products.

Even though index-based weather insurance has unusual promise as an institutional innovation, the major issues of low farmer's demand and high subscription cost might naturally be hindering its implementation beyond the experimental stage. However, our research leads towards meso-insurance products as a credible alternative since it requires communities, or administrative divisions involvement to subscribe for the insurance policy rather than individuals. Given the potential that a meso-insurance product can offer in terms of sustainability, we suggest implementing meso-insurance programs to facilitate a rapid expansion of nationwide flood insurance products in developing countries in the near future.

Therefore, developing countries should use institutional-level insurance. As we already mentioned, individual-level insurance has met with low uptake while there are good reasons why institutions may want to index-insure their portfolios at risk. This includes cooperatives with shared fixed costs, banks with outstanding loans, development agencies with a commitment to deliver expeditiously social protection at a time of crisis and state governments with a legal obligation to provide relief to farmers. Index insurance payouts can be distributed internally to the institution to compensate for locally observable idiosyncratic risks, thus reducing basis risk and improving the quality of the index insurance product Collier and Dercon (2014). Policy questions should be directed at the way these institutions manage basis risk, distribute premium payments to their members, and add a layer of verifiable loss-based transfers to index insurance.

8 Conclusion

In this paper we identify the impact of flood insurance on farmers' productivity by exploiting a natural experiment that took place in three districts of Bangladesh. There are two main empirical results. First, the productivity of a household living in an area covered by the flood insurance scheme increases by roughly 4% after the program is implemented. It is important to note that our result holds for a short-term horizon. Second, our findings reveal that individual-specific fixed effects do not influence the farmers' agricultural productivity.

The findings seem to confirm that the introduction of a flood insurance program will help improve the productivity in the within the area covered by the insurance policy program. Hence, the development of natural disasters products should be considered by policymakers as viable tools for poverty reduction.

We believe further research is needed in at least two dimensions. From my results, we cannot conclude on whether a region hit by flood damages still benefits from the availability of flood insurance programs. Moreover, more work is needed on the national impact of flood insurance programs so that the results of the insurance could possibly affect a larger population.

References

Christopher B Barrett, Barry J Barnett, Michael R Carter, Sommarat Chantarat, James W Hansen, Andrew G Mude, Daniel Osgood, Jerry R Skees, Calum G Turvey, and M Neil Ward. Poverty traps and climate risk: limitations and opportunities of index-based risk financing. 2007.

Hans P Binswanger, Shahidur R Khandker, and Mark R Rosenzweig. How infrastructure and financial institutions affect agricultural output and investment in india. *Journal of development Economics*, 41(2):337–366, 1993.

Jing Cai and Changcheng Song. Insurance take-up in rural china: Learning from hypothetical experience. 2012.

Jun Cai and Wei Wei. Optimal reinsurance with positively dependent risks. *Insurance: Mathematics and Economics*, 50(1):57–63, 2012.

Miguel A Carriquiry and Daniel E Osgood. Index insurance, probabilistic climate forecasts, and production. *Journal of Risk and Insurance*, 79(1):287–300, 2012.

Michael R Carter and Christopher B Barrett. The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies*, 42(2): 178–199, 2006.

Michael R Carter, Francisco Galarza, and Stephen Boucher. Underwriting area-based yield insurance to crowd-in credit supply and demand. *Savings and Development*, pages 335–362, 2007.

Robert G Chambers and John Quiggin. Optimal producer behavior in the presence of area-yield crop insurance. *American Journal of Agricultural Economics*, 84(2):320–334, 2002.

Shelley C Clarke, Murdoch K McAllister, Eleanor J Milner-Gulland, GP Kirkwood, Catherine GJ Michielsens, David J Agnew, Ellen K Pikitch, Hideki Nakano, and Mahmood S Shivji. Global estimates of shark catches using trade records from commercial markets. *Ecology letters*, 9(10):1115–1126, 2006.

Shawn Cole, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. Barriers to household risk management: Evidence from india. *American Economic Journal: Applied Economics*, 5(1):104–35, 2013.

Paul Collier and Stefan Dercon. African agriculture in 50 years: smallholders in a rapidly changing world? *World development*, 63:92–101, 2014.

Peter Custers. Bangladesh's flood action plan: a critique. *Economic and Political Weekly*, pages 1501–1503, 1993.

Russell Davidson, James G MacKinnon, and Russel Davidson. Heteroskedasticity-robust tests in regressions directions. In *Annales de l'INSEE*, pages 183–218. JSTOR, 1985.

Francesca De Nicola. The impact of weather insurance on consumption, investment, and welfare. *Quantitative Economics*, 6(3):637–661, 2015.

Amy Finkelstein and Kathleen McGarry. Multiple dimensions of private information: evidence from the long-term care insurance market. *American Economic Review*, 96 (4):938–958, 2006.

Sarthak Gaurav, Shawn Cole, and Jeremy Tobacman. Marketing complex financial products in emerging markets: Evidence from rainfall insurance in india. *Journal of marketing research*, 48(SPL):S150–S162, 2011.

Xavier Giné and Dean Yang. Insurance, credit, and technology adoption: Field experimental evidencefrom malawi. *Journal of development Economics*, 89(1):1–11, 2009.

RV Hill and A Viceisza. An experiment on the impact of weather shocks and insurance on risky investment. ifpri discussion papers 974. *International Food Policy Research Institute*, 2010.

Sarah A Janzen and Michael R Carter. The impact of microinsurance on asset accumulation and human capital investments: Evidence from a drought in kenya. *ILO Microinsurance Innovation Facility*, 2013.

Dean Karlan, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2):597–652, 2014.

Nan M Laird and James H Ware. Random-effects models for longitudinal data. *Biometrics*, pages 963–974, 1982.

Elaine M Liu. Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china. *Review of Economics and Statistics*, 95(4):1386–1403, 2013.

Olivier Mahul. Managing catastrophic risk through insurance and securitization. *American Journal of Agricultural Economics*, 83(3):656–661, 2001.

Maurizio Mazzocco and Shiv Saini. Testing efficient risk sharing with heterogeneous risk preferences. *UCLA CCPR Population Working Papers*, 2017.

Ahmed Mobarak and Mark Rosenzweig. Selling formal insurance to the informally insured. 2012.

Francesca Nicola. The impact of weather insurance on consumption, investment, and welfare. *Quantitative Economics*, 6(3):637–661, 2015.

Martin Ravallion and Lorraine Dearden. Social security in a" moral economy": An empirical analysis for java. *The Review of Economics and Statistics*, pages 36–44, 1988.

Mark R Rosenzweig. Risk, implicit contracts and the family in rural areas of low-income countries. *The Economic Journal*, 98(393):1148–1170, 1988.

Mark R Rosenzweig and Oded Stark. Consumption smoothing, migration, and marriage: Evidence from rural india. *Journal of political Economy*, 97(4):905–926, 1989.

Mark R Rosenzweig and Kenneth I Wolpin. Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in india. *Journal of political economy*, 101(2):223–244, 1993.

Michael Rothschild and Joseph Stiglitz. Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. In *Uncertainty in economics*, pages 257–280. Elsevier, 1978.

Robert M Townsend. Risk and insurance in village india. *Econometrica: Journal of the Econometric Society*, pages 539–591, 1994.

Appendix

Table 1: Statistics of Gaibanda and Bogra in 2011

	Obs.	Gaibanda	Obs.	Bogra
Average latitude	86	25.35	109	24.82
Average longitude	86	89.5	109	89.34
Average rainfall level January	86	5.33	109	5.39
Average rainfall level May	86	355.37	109	214.57
Average rainfall level December	86	2.81	109	3.27
NDVI January	86	0.3	109	0.4
NDVI June	86	0.51	109	0.48
NDVI December	86	0.4	109	0.39

Table 2: Statistics Of Sirajgonj and Jamalpur in 2011

	Obs.	Sirajgonj	Obs.	Jamalpur
Average latitude	55	24.31	95	24.94
Average longitude	55	89.57	95	89.88
Average rainfall level January	55	7.57	95	5.87
Average rainfall level May	55	220.2	95	332.42
Average rainfall level December	55	1.59	95	2.21
NDVI January	55	0.37	95	0.34
NDVI June	55	0.57	95	0.55
NDVI December	55	0.437	95	0.455

Table 3: Statistics of Borgona and Patuakhali in 2011

	Obs.	Borgona	Obs.	Patuakhali
Average latitude	91	22.15	88	22.26
Average longitude	91	90.13	88	90.4
Average rainfall level January	91	5.45	88	3.82
Average rainfall level May	91	325.54	88	333.3231
Average rainfall level December	91	2.27	88	3.62
NDVI January	91	0.37	88	0.3515
NDVI June	91	0.54	88	0.5633
NDVI December	91	0.53	88	0.499

Table 4: Summary Statistics Of Bogra in 2011

Age Range	Number Of Observations	Mean	Min	Max
member under 6	111	0.4504505	0	2
member male under 16	111	0.7117117	0	2
male members	111	2.072072	0	4
female members	111	2.108108	1	5
members under 15	111	1.378378	0	4
members 15 to 44	111	1.891892	0	4
members 45 to 65	111	0.7117117	0	2
members 65 plus	111	0.1891892	0	2
female members under 16	111	0.7567568	0	4

Table 5: Summary Statistics Of Gaibanda in 2011

Age Range	Number Of Observations	Mean	Min	Max
member under 6	88	0.6022727	0	2
member male under 16	88	0.9545455	0	3
male members	88	1.965909	0	4
female members	88	1.943182	1	5
members under 15	88	1.625	0	4
members 15 to 44	88	1.590909	0	4
members 45 to 65	88	0.5454545	0	2
members 65 plus	88	0.1363636	0	2
female members under 16	88	0.7159091	0	3

Table 6: Summary Statistics Of Jamalpur in 2011

Age Range	Number Of Observations	Mean	Min	Max
member under 6	96	0.46875	0	2
member male under 16	96	0.7083333	0	3
male members	96	1.604167	0	4
female members	96	1.697917	1	4
members under 15	96	1.208333	0	5
members 15 to 44	96	1.40625	0	4
members 45 to 65	96	0.5104167	0	2
members 65 plus	96	0.1666667	0	2
female members under 16	96	0.5625	0	3

Table 7: Summary Statistics Of Sirajgonj in 2011

Age Range	Number Of Observations	Mean	Min	Max
member under 6	57	0.6491228	0	3
member male under 16	57	0.9122807	0	3
male members	57	2.157895	1	5
female members	57	2.280702	1	6
members under 15	57	1.894737	0	5
members 15 to 44	57	1.859649	0	4
members 45 to 65	57	0.5087719	0	2
members 65 plus	57	0.1754386	0	2
female members under 16	57	1.017544	0	4

Table 8: Summary Statistics Of Patuakhali in 2011

Age Range	Number Of Observations	Mean	Min	Max
member under 6	90	0.4888889	0	2
member male under 16	90	0.8777778	0	2
male members	90	2.011111	0	4
female members	90	2.077778	1	5
members under 15	90	1.388889	0	4
members 15 to 44	90	1.511111	0	4
members 45 to 65	90	.7888889	0	2
members 65 plus	90	0.4	0	2
female members under 16	90	0.6	0	4

Table 9: Summary Statistics Of Borgona in 2011

Age Range	Number Of Observations	Mean	Min	Max
member under 6	92	0.5217391	0	2
member male under 16	92	0.6630435	0	2
male members	92	1.847826	0	4
female members	92	1.98913	1	5
members under 15	92	1.293478	0	3
members 15 to 44	92	1.717391	0	4
members 45 to 65	92	0.6847826	0	2
members 65 plus	92	0.1195652	0	2
female members under 16	92	0.6847826	0	4

Table 10: Random effects Regression

	(1)
	log_qty_harvested
Insurance	-0.448**
	(-2.68)
after	0.564***
	(4.26)
Insuranceafter	0.408*
	(2.12)
household_size	0.157**
	(3.17)
married	0.345
	(0.50)
widow	0.154
	(0.20)
divorced	-1.010
	(-0.58)
separated	-0.194
	(-0.13)
Hindu	-0.728*
	(-2.31)
male_head	0.876***
	(3.49)
reads_class1	1.398*
	(2.04)
completed_class1	-0.120
	(-0.23)
completed_class2	0.375
	(1.08)
completed_class3	0.877*
	(2.45)
completed_class4	0.527
	(1.66)
completed_class5	0.595*
	(2.42)
completed_class6	0.139
	(0.23)
completed_class7	0.325
	(0.83)
completed_class8	0.712*
	(2.10)
completed_class9	1.212***
	(3.90)
completed_dhakil	0.812*
	(2.56)
completed_hsc_alim	0.944*
	(1.96)
ba_bsc	2.088*
	(2.31)
ba_bsc_honors	0.614
	(0.37)
ma_msc_and_above	0.183
	(0.15)
preschool_class_gen	1.178
	(0.73)
_cons	4.469***
	(6.02)
N	886

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Robust Regression

	(1)
	log_qty_harvested
Insurance	-0.448*
	(-2.38)
after	0.564***
	(4.51)
Insuranceafter	0.408*
	(2.29)
household_size	0.157***
	(3.29)
married	0.345
	(0.43)
widow	0.154
	(0.18)
divorced	-1.010
	(-1.24)
separated	-0.194
	(-0.21)
Hindu	-0.728*
	(-2.13)
male_head	0.876***
	(3.65)
reads_class1	1.398***
	(3.93)
completed_class1	-0.120
	(-0.25)
completed_class2	0.375
	(1.07)
completed_class3	0.877**
	(2.84)
completed_class4	0.527
	(1.66)
completed_class5	0.595**
	(2.64)
completed_class6	0.139
	(0.19)
completed_class7	0.325
	(0.87)
completed_class8	0.712*
	(2.02)
completed_class9	1.212***
	(4.32)
completed_dhakil	0.812*
	(2.40)
completed_hsc_alim	0.944
	(1.87)
ba_bsc	2.088***
	(4.69)
ba_bsc_honors	0.614***
	(4.83)
ma_msc_and_above	0.183
	(0.14)
preschool_class_gen	1.178***
	(9.43)
_cons	4.469***
	(5.31)
N	886

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$