Insuring against droughts: Evidence on agricultural intensification and index insurance demand from a randomized evaluation in rural Bangladesh*

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Abstract

This study assesses both the demand for and effectiveness of an innovative index insurance product designed to help smallholder farmers in Bangladesh manage risk to crop yields and the increased production costs associated with drought. Villages were randomized into either an insurance treatment or a comparison group, and discounts and rebates were randomly allocated across treatment villages to encourage insurance take-up and to allow for the estimation of the price-elasticity of insurance demand. Among those offered insurance, we find insurance demand to be moderately price elastic, with discounts significantly more successful in stimulating demand than rebates. Farmers that are highly risk averse or sensitive to basis risk prefer a rebate to a discount, suggesting that the rebate may partially offset some of the implicit costs associated with insurance contract nonperformance. Having insurance yields both ex ante risk management effects as well as ex post income effects on agricultural input use. The risk management effects lead to increased expenditures on inputs during the *aman* rice growing season, including for risky inputs such as fertilizers, as well as for irrigation and pesticides. The income effects lead to increased seed expenditures during the *boro* rice growing season, which may signal insured farmers' higher rates of seed replacement which broadens access to technological improvements embodied in newer seeds, as well as enhancing the genetic purity of cultivated seeds.

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1 Introduction

Agricultural production in developing countries is fraught with various sources of risk. The type and severity of these risks varies by crop or farming system, agroecological conditions, and the policy and institutional settings (Hazell et al., 1986). A seemingly ubiquitous source or agricultural risk is production risk due to weather uncertainty and variability, particularly those associated with deficient rainfall. There are various strategies that can be taken to mitigate such drought risks, including investments in infrastructure (e.g., irrigation facilities), technological innovations (e.g., drought-tolerant cultivars), crop management practices (e.g., changes to the timing of production activities or reductions in crop durations), and financial instruments (e.g., credit or insurance). Unfortunately most of these strategies are often either not available or not feasible for many resource-poor farmers in developing countries. Consequently, not only do droughts often result in lower crop productivity, but the risk of drought provides a disincentive for otherwise optimal investments in new technologies and modern farm inputs (Sandmo, 1971; Quiggin, 1992). While these management decisions may reduce income or consumption variability in the short run, they also constrain the farmer's long-run growth potential.

In this paper we focus on insurance, and assess the degree to which insurance markets can be developed for resource-poor farmers in low income settings, and incentivize optimal agricultural investments. Conventional indemnity-based crop insurance – which insures farmers against assessed crop losses – is problematic due to asymmetric information (resulting in moral hazard and adverse selection) and high transaction costs (Hazell, 1992; Morduch, 2006; Barnett et al., 2008). Index insurance, on the other hand, provides insurance coverage on the basis of observed indices, such as weather conditions measured at a local weather station or average yields in a given area, rather than directly assessed individual yield or profit losses (Giné et al., 2008; Karlan and Morduch, 2009; Morduch, 2006). As index-based insurance does not require verification or assessment of losses at the farm level, it minimizes asymmetric information and drastically reduces the delays and costs associated with conventional crop insurance, including both administrative and re-insurance costs (Barnett and Mahul, 2007). For these reasons, many development practitioners and policymakers are cautiously optimistic about the potential for index insurance to stimulate agricultural investment and productivity (Alderman and Haque, 2007; Hazell et al., 2010).

Because payouts are made on the performance of an index, however, they are not always commensurate with the losses that a farmer has experienced, and this leads to basis risk – the risk that the farmer experiences a loss and receives no insurance payout because it is not a loss that is reflected in the index (Clarke, 2016). As a result of this and other factors that constrain demand (such as liquidity constraints, limited knowledge of the product, lack of trust in insurance providers; see Cole et al., 2013; Giné et al., 2008; Giné and Yang, 2009; Hill et al., 2016), many of the index insurance programs that have been piloted to date have met with limited success (e.g., see the review in Binswanger-Mkhize, 2012). When insurance is adopted at reasonable scale, however, much of the emerging evidence suggests it is successful in encouraging agricultural investment (Karlan et al., 2014; Elabed and Carter, 2015; Mobarak and Rosenzweig, 2013; Berhane et al., 2014).

This study assesses both the demand for and effectiveness of an innovative index insurance product designed to help smallholder farmers in Bangladesh manage risk to crop yields and the increased production costs associated with drought. While most observers might not think of Bangladesh as being particularly prone to droughts, droughts are observed to cause significant damage to an estimated 2.32 million hectares of the transplanted *aman* (monsoon season rice) crop each year, with serious nationwide droughts occurring roughly once every five years (Ramamasy and Baas, 2007). The widespread increase in the availability and use of irrigation in recent years has allowed Bangladeshi farmers to mitigate the impact of drought on production, but the use of irrigation to do so is costly, such that rainfall deficiencies can ultimately result in significant increases in the costs of production, in addition to any residual impacts on yields. These risks associated to production costs and farm profits may be masked in any index that is solely focused on yields, despite the fact that profit risks may be the most salient to farmers making decisions about costly and risky inputs. To address these risks, the index insurance product that we evaluate in the present study was designed to provide payouts primarily on the number of consecutive dry days that were observed during the monsoon season. But since there is an imperfect correlation between weather conditions and crop production, such an index insurance product necessarily implies nontrivial basis risk. Because area yield indices are agnostic regarding the cause of the yield losses, many have advocated the use of such indices where possible in order to reduce basis risk. Indeed, average area yield is the index used in most index-insurance products sold in Asia (Clarke, 2016; Cai, 2016). The product that we evaluate in the present study therefore incorporated an area yield index that could potentially be triggered if the dry-day index were not triggered. To our knowledge, this is the first study to evaluate a product designed to cover both yields and costs to production.

The randomized controlled trial (RCT) described here was designed to evaluate a local non-governmental organization's (NGO) index insurance pilot program in Bogra district in northwestern Bangladesh during the 2013 *aman* season. While not directly tied to rice production, the insurance product was intended to cover production risks on a 10 decimal (0.1 acre) plot of land during the *aman* season. Discounts and rebates were randomly allocated to villages to encourage insurance take-up, to allow the price-elasticity of demand to be calculated, and to evaluate the trade-off between providing discounts and rebates. A priori, one might expect that discounts would be preferred to rebates given they help address liquidity constraints at the time of insurance purchase. Additionally, there is evidence from various studies in several developing countries that suggest individuals value the present more than the future, and would therefore prefer the immediate benefit of a discount to the delayed benefit of a rebate. Along similar lines, individuals may prefer the discount because there is more certainty associated with a discount now, whereas the promise of a rebate in the future entails some uncertainty. Interestingly, however, despite the uncertainty, this promise of a future payment may be alluring for some farmers. In the context of insurance rebates provide a certain payout in the future regardless of whether the insurance pays out, and this has been shown to be preferred in Burkina Faso (Serfilippi et al., 2016).

We find insurance demand to be moderately price elastic. The incentives offered were quite high, and as a result, a large proportion of households purchased at least one unit of insurance. Discounts were significantly more successful in stimulating demand than rebates, which entail a sizable lag between when the purchase is made and when the benefits of the incentive are realized. The price elasticity implied by the results suggests that there would need to be a 14 percent discount or a 34 percent rebate relative to the actuarially fair price of insurance in order to observe purchases of a single unit of insurance. It is possible that the discounts required to sustain demand would fall over time as farmers came to know and value the product, but the high level of discount required suggests an unsubsidized private crop insurance market could not persist in Bangladesh. Despite the preference for discounts in aggregate, we find some significant heterogeneity in demand responses to a rebate, suggesting that some individuals, particularly those that are especially risk-averse or sensitive to basis risk, may implicitly view the rebate as a commitment savings mechanism that can offset the costs of insurance contract nonperformance, especially if they experience an on-farm loss and yet are not indemnified by the insurance.

Consistent with theory, insurance resulted in increased investment in risk-increasing agricultural inputs during the *aman* rice-growing season. The coverage of the cost of production risk in the insurance contract also increased use of irrigation to mitigate the yield impact of the long dry spell that was recorded in the 2013 *aman* season. Somewhat surprisingly an increase in pesticide use was also recorded, indicating that index insurance is not plagued by the same problems of moral hazard as indemnity insurance. The dry spell in the 2013 *aman* season was long enough to trigger an insurance payment which were disbursed prior to land preparation in the subsequent *boro* rice-growing season. The disbursement of insurance payments provided farmers with a liquidity injection that led to increased investments in risk-increasing modern agricultural inputs related to *boro* production. While there was no significant effect on rice production or productivity during the *aman* season, we find that the increased investment in modern inputs during the *boro* season led to a roughly 8 percent increase in *boro* production.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review on the determinants of insurance demand and the impacts of index-based insurance – particularly on investments in modern agricultural inputs. Section 3 describes the experimental context, the insurance product, and our experimental design. Section 4 presents the empirical results on determinants of insurance demand and in Section 5 we present findings on the impact of insurance on agricultural input use. In Section 6, we offer some concluding thoughts and reflections, and discuss the policy implications of our findings.

2 Review of the literature on the impacts of insurance and determinants of insurance demand

Insurance is expected to have both ex post as well as ex ante impacts on farm households. The ex post benefit of insurance arises as households' trade income in good states of the world with income in bad states of the world. When insurance is actuarially fairly priced, this will result in welfare gains for any risk-averse individual. The ex-ante impacts are more nuanced, and are associated with the expected effects of risk transferal on farmers' production decisions. Dating back to Sandmo (1971), there has been at least a theoretical understanding that risks act as an impediment to what would otherwise be profit-maximizing investments. While Sandmo (1971) is primarily concerned with producer behavior under output price risk, Quiggin (1992) demonstrates a similar result with respect to production risk, which, in many ways, is the most salient source of risk faced by smallholder farmers in developing countries. Quiggin (1992) shows that input use responses to risk depend crucially on the risk preferences of the producer and the risk profile of the input. Unsurprisingly, risk-neutral producers behave as predicted by expected utility theory. Under production risk, risk-averse producers increase input demand for risk-reducing inputs (e.g., pesticides) and reduce input demand for risk-increasing inputs (e.g., fertilizers) relative to risk neutral producers. This indicates that, assuming the inputs are not costless, insurance increases overall exposure to high production outcomes for risk averse producers. The theoretical results are ambiguous for mildly risk-increasing inputs, and depend upon the marginal product of the input and its subsequent impact on the countervailing risk and moral hazard effects.

Despite frequently strong theoretical arguments for insurance, attempts to provide formal, indemnity-based crop insurance in many developing countries have struggled, arguably due to poor contract performance, asymmetric information, high transaction costs, and high exposure to covariate risks (Barnett et al., 2008; Hazell, 1992; Carter et al., 2016; Binswanger-Mkhize, 2012). To circumvent some of these impediments, policymakers and development practitioners have turned to index-based insurance programs, which base insurance payments on the performance of some transparent, easy-to-measure index relative to some benchmark.

Index-based insurance products have several advantages over traditional crop insurance (e.g., Miranda, 1991). First, payments are based on index triggers that are typically easy to observe and measure, making the index more transparent to the insured, minimizing asymmetric information between the insured and insurer, and reducing the probability of adverse selection and moral hazard (Clarke et al., 2015). This allows for payments to be calculated easily and distributed in a timely manner. Additionally, because insurance payments are based on an index rather than loss adjustments calculated for each farm that is insured, operating and administrative costs may be significantly lower than those of other types of agricultural insurance (Barnett et al., 2008). Along the same lines, contracts can be standardized and need not be tailored to the individual needs of different policyholders (Skees, 2008). Finally, because the index triggers are independently measured and easily verifiable, local context knowledge becomes relatively unimportant, so it is easier for reinsurers to understand risks (Alderman and Haque, 2007). Within much of the development practitioner and donor community, index insurance is seen as having the potential to provide vulnerable farming households with an important and valuable type of safety net that can stimulate agricultural growth and development (Hazell et al., 2010).

Despite these benefits, however, index-based insurance is hardly a panacea. Farmers only receive compensation when the level of the index relative to some threshold triggers payouts. Since most indices are tied to observable weather outcomes which are only imperfectly correlated with on-farm losses (e.g., Rosenzweig and Binswanger, 1993), there is a nontrivial probability that farmers will not be compensated even when they realize significant on-farm losses. Perils unrelated to the index such as soil conditions, pest and disease infestations, and farmer illness also affect yields. The residual risk that a farmer may incur a large loss and still not receive any payment from the insurance contract (e.g., if weather conditions on the farmer differ from those at the weather station at which the index components are measured) is referred to as basis risk, and has been shown to pose a major deterrent to index insurance uptake (Clarke, 2011; de Nicola, 2015; Hill et al., 2013; Mobarak and Rosenzweig, 2012).[1] Indeed, across various countries and contexts, uptake of index

[1] While basis risk is commonly conceptualized as the mismatch between weather conditions on farmers' fields and those at the weather station or other site at which the weather variables constructing the index are measured, basis risk more broadly refers to any genesis of insurance contract non-performance, which, in this case, refers to any farm losses not compensated for, including – but not limited to – those arising due to the aforementioned mismatch in

insurance has been low, even when offered at better-than-competitive rates.[2]

Among the many reasons cited for low take-up of index insurance products are those related to liquidity constraints, basis risk, trust in the insurance provider, and temporal disparities between when premiums are due and when potential payouts are received. An important feature of insurance contracts, particularly as they pertain to resource-poor farmers, is that they entail a current cash outflow with the potential for an uncertain payout in the future. This can be a significant deterrent to demand for insurance among individuals who are liquidity constrained. Trust in the insurance provider also becomes important, and those same individuals are likely to demand insurance only if they have a relatively high confidence that the insurance claims will actually be honored if due (e.g., Karlan et al., 2014).

As a normal good, both the individual demand for an insurance policy and the cumulative sales of insurance policies should be declining in the price of the insurance policy. Indeed, this is one of the few empirical regularities, though admittedly with varying degrees of consistency across contexts. Cole et al. (2013) found insurance demand in the Indian states of Andhra Pradesh and Gujarat to be highly price elastic, with a 10 percent reduction in the price of insurance associated with a 10-12 percent increase in insurance take-up. Numerous other studies also emphasize the role of monetary encouragements in increasing insurance demand. In their study in Ethiopia, McIntosh et al. (2013) found that 25 percent of those randomly allocated to an insurance treatment group ultimately took up insurance, but the evidence suggests that demand might have been non-existent in the absence of a sizable subsidy. Karlan et al. (2014) find that 40-50 percent of Ghanaian farmers purchased insurance at actuarially fair prices, but take-up rates dropped to 10-20 percent when charged double the actuarially fair price. Mobarak and Rosenzweig (2012) find the price elasticity of insurance demand to be -0.44 and citetHill2016 estimate the price elasticity as -0.58.

Beyond price, other factors affect demand for insurance. Demand for indemnity insurance is increasing in the degree of risk aversion, increasing in the expected payout, and increasing in the size of the insured risk (i.e., the magnitude of the potential losses) (e.g., de Nicola, 2015; Clarke,

weather conditions.

[2] A prominent counterexample to this widely observed phenomenon is the study by Karlan et al. (2014) in Ghana. Even at the actuarially fair price, 40 to 50 percent of the farmers in their sample demanded insurance, and on average purchased coverage for more than 60 percent of their cultivated area.

2016). In the presence of basis risk insurance demand is initially increasing in risk aversion before decreasing such that, for very risk-averse farmers, purchasing insurance actually makes them *worse* off (Clarke, 2016). This phenomenon captures decision makers trading off the benefits of the increase in expected wealth when the index insurance contract performs (e.g., under scenarios in which on-farm conditions match those at the weather station at which the index is measured) against the cost of basis risk when the contract does not perform (particularly states in which the farmer experiences on-farm losses yet the index is not triggered).

Empirical evidence further substantiates these theoretical claims. Hill et al. (2016) find that demand for index insurance is inverse U-shaped in risk aversion, with price sensitivity decreasing at higher levels of basis risk. Mobarak and Rosenzweig (2012) find that, for every kilometer increase in the perceived distance of a farmer's land from the weather station, the demand for index-based insurance dropped by over 6 percent. Hill et al. (2016) find that doubling the distance to the reference weather station decreases demand by 18 percent. Similarly, using willingness to pay estimates in Ethiopia, Hill et al. (2013) find an inverse relationship between basis risk and insurance demand, especially at high prices. Based on a discrete choice experiment in eastern India, Ward and Makhija (2016) find that, for every 1 percent increase in basis risk, farmers would need to be compensated with a 3-4 percent reduction in the cost of insurance.

Understanding the determinants of insurance demand are important for the development of a viable insurance market. But if insurance does not induce investments in higher risk, higher return activities, then insurance essentially yields little value, and may not merit public support using scarce resources. Fortunately, in cases where sufficient uptake of insurance has occurred, impacts of index-insurance have largely been positive (Carter et al., 2014). Evidence from multiple empirical studies support the underlying hypotheses that insurance increases household consumption and incentivizes farmers to take greater risks, spend more on their farms, and realize the benefits of higher yields or output. Using data from an RCT on an innovative micro insurance product in Kenya, Janzen and Carter (2013) find that insurance positively affects pastoral farm households following a shock: asset-rich households are less likely to engage in distress sales of livestock to smooth consumption, while asset-poor households are less likely to destabilize consumption by reducing meals. Hill and Viceisza (2012) use games to hypothetically answer the question of whether insurance encourages farmers to take great, yet profitable, input use risks and found a positive impact of insurance on fertilizer purchase. Karlan et al. (2014) found that insurance led Ghanaian farmers to increase agricultural expenditures on their farms along both the extensive as well as the intensive margin. In particular, they found that insured farmers cultivated nearly an acre more land and spent nearly 14 percent more on land preparation costs (increasing along the extensive margin), while simultaneously increasing expenditures on modern inputs (mostly fertilizers) by nearly 24 percent (increasing along the intensive margin). In Andhra Pradesh, India, Cole et al. (2013) find that insurance causes farmers to invest in higher-return – albeit rainfall-sensitive – cash crops. In Tamil Nadu, India, Mobarak and Rosenzweig (2012) find that farmers who are insured shift to high-yielding rice varieties over lower-yielding, drought-tolerant ones. They also find that formal insurance is an enabling factor in households' risk-taking decisions. In the context of a field experiment in Senegal and Burkina Faso, farmers who purchased more weather index insurance had higher average yields and were better able to manage food insecurity and shocks (Delavallade et al., 2015). Berhane et al. (2014) find that fertilizer use is 13 percentage points higher among insured farmers in Ethiopia.

3 Study context and experimental design

3.1 Context and overall study design

This study took place in Bogra district of Rajshahi Division in northwestern Bangladesh. Bogra is largely rural and livelihoods are heavily dependent upon agriculture, with rice double-cropping the predominant cropping system. While much of Bogra is characterized by alluvial soils fertilized by siltation from floodwaters, much of it is simultaneously drought-prone: farmers in Bogra identified drought and crop diseases as the major sources of crop loss during *aman* season (Clarke et al., 2015). During the annual monsoon season, in which Bangladesh receives roughly 80 percent of its annual rainfall, there are three distinct types of droughts. Early season droughts arise due to the delayed onset of the annual monsoon and can affect the timing of activities such as transplanting, which in turn affects both the area cultivated and yields. Mid-season droughts typically arise as intermittent, prolonged dry spells and, depending on their timing, reduce crop productivity. Finally, late-season droughts arise due to early monsoon cessation and are particularly damaging for rice production, as they tend to coincide with flowering and grain filling stages in the crop growth cycle.

The study was implemented with the cooperation of a local NGO, Gram Unnayan Karma (GUK), that provides a range of services to households in Bogra, including microfinance, non-formal primary education, primary healthcare, and women's empowerment activities. GUK was established in 1989 and operates primarily through village-level groups consisting of female "members" who voluntarily register to participate and benefit from GUK activities. The study was initiated with a baseline survey in the spring of 2013 and culminated with a follow-up survey just more than 12 months later (see Figure 1).

Three *upazilas* (subdistricts) within Bogra were selected on the basis of proximity to the district meteorological station operated by the Bangladesh Department of Meteorology (Figure 2). Within each of the three selected *upazilas*, 40 villages were randomly selected for inclusion in the study. From within each of these 120 villages, a sample of GUK members (averaging between 15 and 20 members per village) was randomly selected to participate in the study. The baseline survey proceeded in May 2013 among the total sample of 2,300 households from these 120 villages.[3] GUK marketed the index insurance product (described in greater detail below in Section 3.2) in half of the sample villages (the randomly-assigned treatment villages) from late May until late June. The coverage period for the insurance policy ran from mid-July to mid-October, as described below. Payouts were made in November 2013 and follow-up surveys were conducted from June to July 2014. All told, attrition proved to be a very minor concern, as virtually all (97 percent) of the households interviewed during the baseline survey were also interviewed during the follow-up survey.[4]

Table 1 presents average characteristics of households in our sample by treatment category. By and large, there are few systematic differences between households in treatment villages and those in comparison villages, which bodes well for subsequent efforts to econometrically identify treatment

[3]While the initial sample consisted of 2,300 agricultural households, in the ensuing analysis the sample is restricted to include only those that cultivated rice, the predominant crop in Bangladesh

[4]While there was very little attrition between baseline and follow-up, the sample sizes that emerge in Tables 1, 4, 5, and 6 are smaller than the original sample due to missing observations on key data.

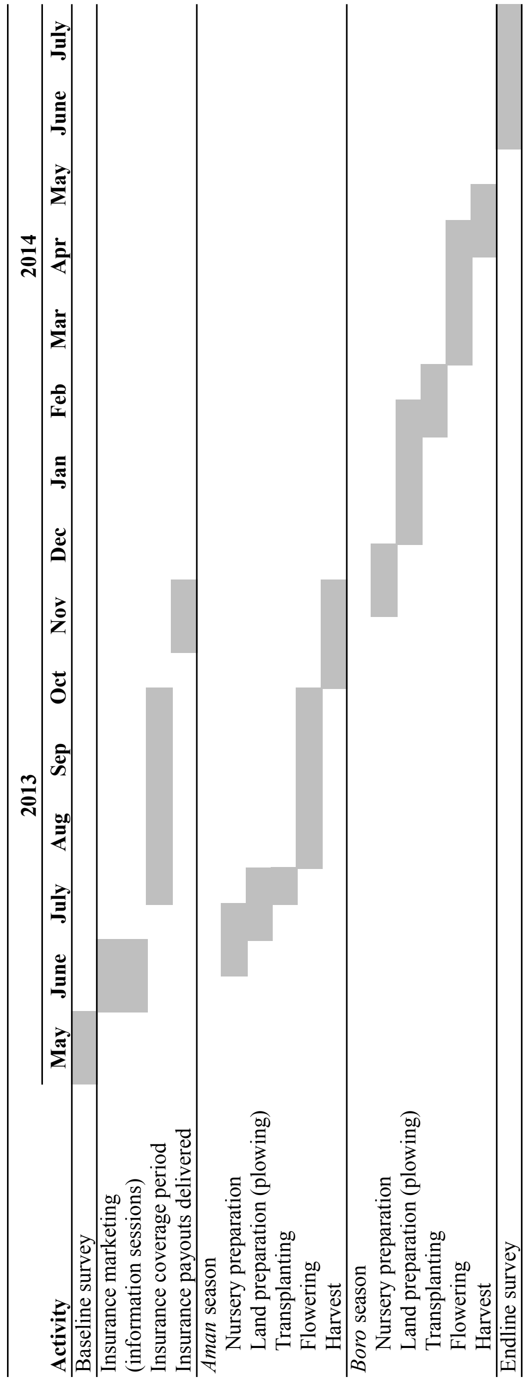

Figure 1: Timeline of research and agricultural activities during study period

Source: Authors.
Note: Agricultural timeline based on focus group discussions carried out prior to the initiation of the study and reflect consensus opinions of focus group members. Due to various factors, including weather conditions, soil variability, seed varieties, labor supply constraints, etc., the timing of agricultural activities and crop growth cycles varies.

effects. The overall sample presents the following characteristics on average. Roughly 96 percent of the households are headed by males who, on average, are about 43 years of age. Among these household heads, the number of years of schooling completed averages about 3.5 years. Households own and cultivated NA different plots totaling roughly 94.2 decimals (0.94 acres) of land on all crops in the 12-month recall period prior to the baseline survey in 2013, including 52 decimals cultivated under *aman* rice and 63 cultivated under *boro* rice. A little over a quarter (30 percent) of our sample owns a savings account with a bank, while on average less than 20 percent of households are members of informal savings groups.[5] Nearly all (NA percent) households had taken a loan in the 12-month recall period prior to the baseline survey. All these indicate familiarity with financial products and formal institutions, and suggest some basic capacity to understand the insurance product.

Households in our sample have been GUK members for about 4 years, though those who reside in villages randomly allocated to the insurance treatment group have a slightly shorter legacy than those residing in villages randomly allocated to the comparison group (3.6 years vs. 4.1 years). The fact that households in the treatment villages have typically maintained a relationship with the organization providing insurance is important. The level of trust in our sample was quite high (5.2 on a scale of 0 to 7 where 7 is someone who is completely trusting).[6] Trust in and familiarity with the insurance provider has been shown to be an important determinant of insurance demand and can have implications for uptake (Karlan et al., 2014). The saliency of this characteristic may be magnified for households that are risk-averse. Households in the sample show an average level of partial risk aversion of 3.7, which is classified as severe according to Binswanger (1980).

When considering outcome variables of interest, we note there are few systematic differences in households in treatment and comparison villages along most agricultural dimensions at baseline. Total output and expenditures on seed, fertilizers, and pesticides during the *aman* 2012 season are statistically indistinguishable between treatment and comparison villages, as are all agricultural

[5]Here, we acknowledge that there is a slight imbalance between households in treatment and comparison villages. In our treatment villages, roughly 17 percent of households are members of informal savings groups, compared with about 21 percent of households in the comparison group.

[6]The measure of trust reported here is derived from a simple, equally-weighted index based on responses to a series of scale-response questions about respondents' level of trust in various actors, and were not specific to GUK.

Table 1: Characteristics of households in randomly allocated treatment and comparison villages

	Sample	Comparison	Treatment	Difference
Household characteristics				
Gender of household head (male = 1)	0.96	0.95	0.97	−0.02
	(0.00)	(0.01)	(0.01)	[0.04]
Age of household head	42.73	42.54	42.92	−0.38
	(0.27)	(0.38)	(0.38)	[0.47]
Education (highest class completed) of household head	3.52	3.37	3.66	−0.29
	(0.09)	(0.13)	(0.13)	[0.11]
Total land owned and cultivated (decimal)	94.18	94.61	93.77	0.84
	(1.99)	(2.72)	(2.69)	[0.83]
Number of years household has been a member of GUK	3.84	4.09	3.59	0.50
	(0.07)	(0.10)	(0.10)	[0.00]
Household has a savings account with a formal bank (=1)	0.29	0.30	0.28	0.02
	(0.01)	(0.01)	(0.01)	[0.36]
Household is a member of an informal savings group (=1)	0.19	0.21	0.17	0.04
	(0.01)	(0.01)	(0.01)	[0.04]
Household asset index (PCA)	0.06	0.01	0.10	−0.09
	(0.02)	(0.03)	(0.03)	[0.04]
Partial risk aversion coefficient	3.67	3.66	3.68	−0.02
	(0.07)	(0.11)	(0.10)	[0.91]
Ambiguity averse (=1)	0.29	0.32	0.25	0.07
	(0.01)	(0.01)	(0.01)	[0.00]
Trust index (0 = least trusting; 7 = most trusting)	5.41	5.24	5.57	−0.33
	(0.03)	(0.04)	(0.04)	[0.00]
Aman season 2012				
Total land under *aman* rice (decimals)	52.25	53.76	50.76	3.00
	(1.34)	(1.67)	(1.65)	[0.26]
Total harvest of *aman* rice (kg)	792.44	768.57	815.86	−47.29
	(22.59)	(30.18)	(29.89)	[0.30]
Total expenditures on fertilizers (BDT)	2066.39	2154.57	1979.89	174.68
	(60.24)	(79.54)	(78.78)	[0.15]
Total expenditures on pesticides (BDT)	287.38	290.02	284.78	5.23
	(12.71)	(18.03)	(17.86)	[0.84]
Total expenditures on hired labor (BDT)	1652.49	1763.48	1543.62	219.87
	(61.36)	(70.35)	(69.67)	[0.07]
Total expenditures on irrigation (BDT)	732.71	675.49	788.84	−113.35
	(33.03)	(48.83)	(48.37)	[0.09]
Total expenditures on purchased seeds (BDT)	425.78	421.17	430.31	−9.14
	(20.71)	(26.83)	(26.57)	[0.83]
Boro season 2012-13				
Total land under *aman* rice (decimals)	63.14	64.37	61.93	2.44
	(1.44)	(1.77)	(1.75)	[0.40]
Total harvest of *aman* rice (kg)	1452.11	1451.18	1453.01	−1.83
	(34.40)	(43.21)	(42.80)	[0.98]
Total expenditures on fertilizers (BDT)	4288.60	4204.71	4370.90	−166.20
	(107.88)	(156.84)	(155.34)	[0.44]
Total expenditures on pesticides (BDT)	555.56	532.91	577.77	−44.87
	(31.04)	(55.79)	(55.26)	[0.47]
Total expenditures on hired labor (BDT)	2881.30	2959.90	2804.20	155.70
	(99.18)	(131.54)	(130.28)	[0.43]
Total expenditures on irrigation (BDT)	3014.46	2953.88	3073.89	−120.01
	(72.14)	(103.29)	(102.30)	[0.41]
Total expenditures on purchased seeds (BDT)	983.52	962.92	1003.72	−40.80
	(51.68)	(55.25)	(54.72)	[0.69]
Number of observations	1977	979	998	

Source: Authors.

Notes: Figures in parentheses are standard errors of sample means. Figures in brackets are p-values from parametric tests of differences in sample means.

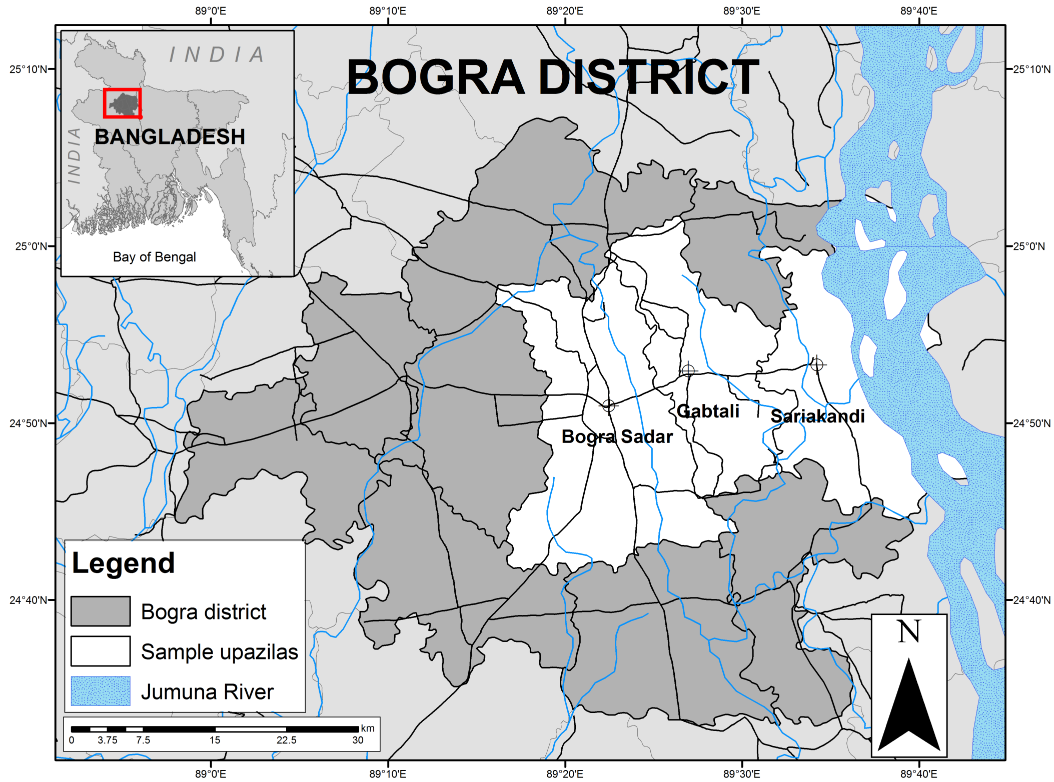

Figure 2: Location of sample *upazilas* in Bogra district, Rajshahi division, Bangladesh

Source: Authors.

outcomes during *boro* 2012-13. Households in the treatment villages did, however, spend less on hired labor and more on irrigation during *aman* production in 2012.

3.2 The insurance product

The insurance policy covered the *aman* season (July 15 - October 14, inclusive), a period characterized by large amounts of rainfall on average, but also with significant variability (Figure 3). While the *aman* rice crop is largely rainfed, we also note that there is widespread evidence of functioning irrigation markets during this season as well, with groundwater irrigation serving to supplement deficient rainfall. The insurance product protected households against a long period of successive "dry-days" during the *aman* season and against low average area yields as a result of overall rainfall deficiency, pests, crop diseases, or flood. [7]

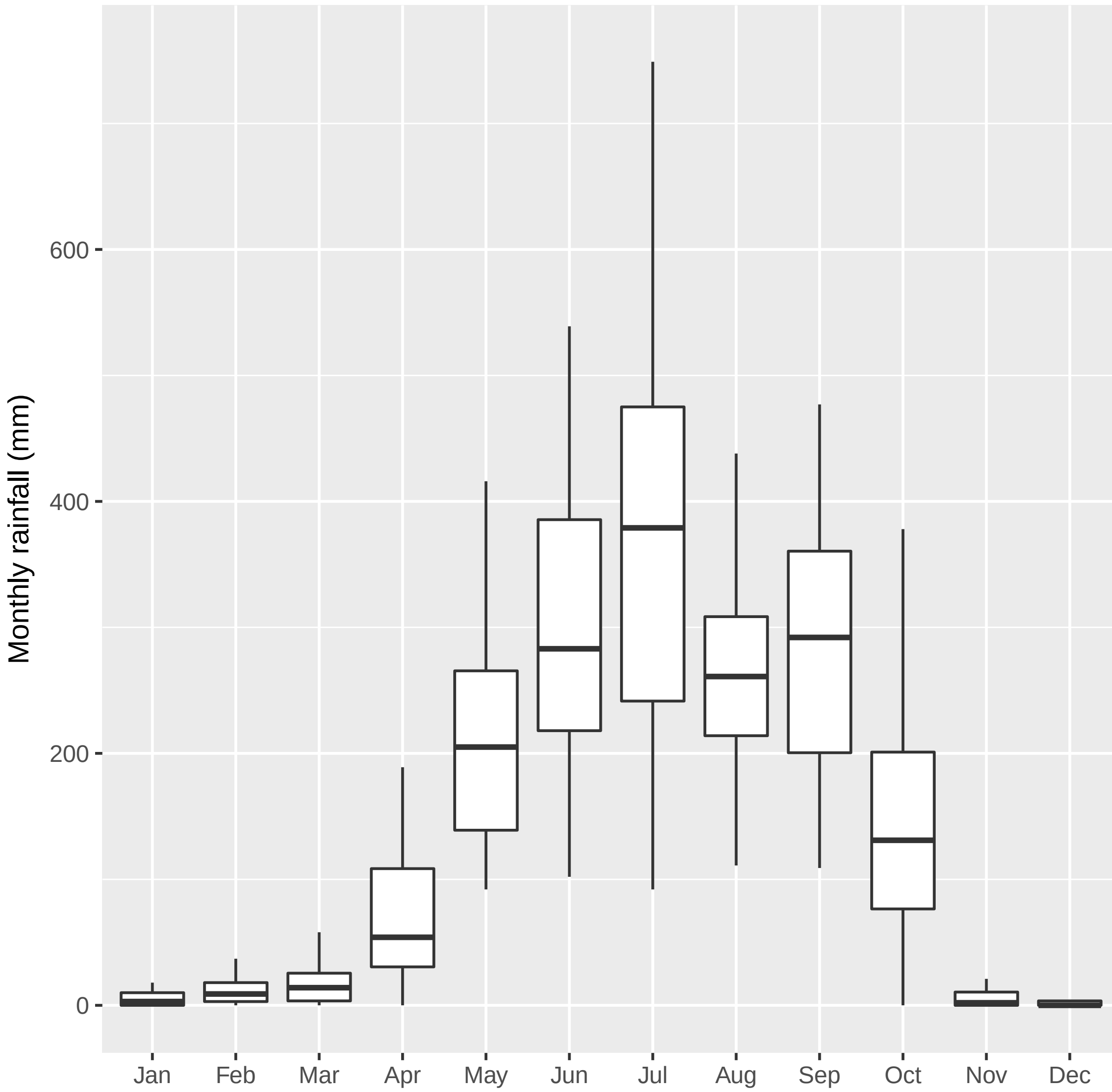

Figure 3: Historical distribution of rainfall by month, Bogra district, Bangladesh

Source: Authors; based on rainfall data from the Bangladesh Meteorological Department weather station in Bogra district, 1980–2010.

According to the policy specifications, the insured would receive a payout if a long period of successive dry days were recorded at the local weather station *or* if the average area yield in the *upazilla* was very low. Table 2 describes these events and how they relate to policy triggers

[7] A "dry-day" is any day in which the cumulative rainfall is less than 2 mm.

and corresponding payouts. The dry days triggers were established based on 30 years' worth of historical rainfall data from the Bangladesh Meteorological Department. If the longest dry spell that occurred was at least a 14-day period, the policy would pay out BDT 600.[8] On average, this type of dry spell occurs roughly once every decade. If the longest dry spell that occurred was a 12- or 13-day dry spell, the policy holder would receive a payment of BDT 300. This type of dry spell occurs roughly once every five years on average.[9] Actual rainfall measurements were recorded at the *upazila* Agricultural Extension Offices in each of the three *upazilas*, allowing for potential heterogeneity in rainfall realizations – and thus the performance of the index insurance product – over space. If the dry days triggers were not met the insurance could still be triggered based on the outcome of a crop-cutting exercise undertaken by Bangladesh Bureau of Statistics at the *upazila* level. If the average yield from 30 randomly selected plots from the *upazila* was less than 26 maunds per acre, the policy would pay out BDT 300.[10] Each policy could pay out a maximum of one time based on the greatest severity of the three events – if any – that occurred.

The base cost per unit of insurance was BDT 100, roughly 10 percent lower than the actuarially fair price. While not directly tied to production, each policy was meant to cover revenue from 10 decimals (0.1 acres) of land cultivated under rice. On average, households in the sample cultivate roughly 50 decimals under *aman* rice during the monsoon season, so each policy unit covers about one-fifth of the rice area cultivated in this season. Each household had the option to purchase multiple units of the insurance based on the amount of land they cultivate during the rain-fed agricultural season. However, they could purchase insurance for cultivated land only, such that a household could not purchase insurance coverage for more land than they cultivated, thereby reducing any incentive to view the insurance as a lottery or gamble.

[8]BDT = Bangladeshi taka. At the time of the intervention, the exchange rate was approximately BDT 76 per USD.

[9]The return periods for these triggers are based on the assumption that the annual maximum dry spell is distributed according to a Generalized Extreme Value distribution. The location, shape, and scale parameters of this distribution were estimated using maximum likelihood and then used to estimate the levels (i.e., dry spell lengths) associated with the associated return periods.

[10]A maund is a unit of mass commonly used in much of South Asia, roughly equivalent to 40 kg.

Table 2: Insurance policy triggers

Event	Triggers	Description of trigger	Payout
First	14 day dry spell	Maximum number of consecutive dry days when the rainfall recorded at the station is less than or equal to 2 mm in the coverage period is 14 or more days	BDT 600
Second	12 day dry spell	Maximum number of consecutive dry days when the rainfall recorded at the station is less than or equal to 2 mm in the coverage period is 12 or 13 days	BDT 300
Third	Average yield in the *upazila* is less than or equal to 26 maunds per acre	Average yield (as estimated by crop cutting experiment conducted at *upazila* by the Bangladesh Bureau of Statistics) is less than or equal to 26 maunds per acre	BDT 300

Source: Authors.

3.3 Insurance marketing

Informational sessions were held in all treatment villages during which trained product specialists from GUK introduced the insurance product. These training sessions were held about two weeks in advance of the actual sales period. The training sessions typically consisted of 15 to 20 participating households, including both the female (GUK member) and her husband or other male family member responsible for decision making. All households that were GUK members within these villages were invited to attend these sessions and were eligible to buy the insurance as long as they cultivated own- or rented-land during the monsoon season. A large percentage of invited households (more than 96 percent for each focus group meeting) attended these sessions.

Each training session lasted 3-4 hours and was designed to provide information to help farmers make well-informed decisions about whether or not to purchase insurance. Each session discussed the nature of risk to agricultural production and the strategies that households could use to cope with these risks. The insurance product that was being offered was described, and discussed the possibility of basis risk. Various hypothetical cases were considered for the purpose of exposition. The session concluded by setting a date and time for the follow-up informational session and how participants could go about purchasing the insurance product, if interested. To simplify the purchasing process, agents distributed insurance demand forms that participants were asked to complete prior to the next appointment.

Since many index insurance programs have suffered from low demand in the past, we were interested in studying the differential effects of alternative incentive mechanisms on stimulating insurance demand. To this end, we randomly allocated half of the villages in the treatment group to receive an instantaneous discount (reduction in the purchase price), while the other half received a rebate (portion of the purchase price refunded at a later date, toward the end of the *aman* season). We further randomized the level of discount or rebate received at the village level with a skewed distribution such that a higher proportion of sample villages were eligible to receive a higher monetary incentive in order to ensure a reasonable demand for the insurance. Table 3 provides the distribution of villages by the level of discount or rebate. Within the rebate group, the timing of receipt of the rebate was further randomized at the individual level. Half of the farmers in the rebate group received the rebate at the end of the agricultural season and the other half received the rebate during a lean season prior to harvest when farmers' cash flow is most constrained.[11]

Participants were informed at the end of the training session that they would be the recipient of discount or rebate. The value of the discount (rebate) the village was to receive was randomly selected in the training session. Thus, participants were aware of the effective purchase price for insurance as well as any future refunds they would be entitled to prior to committing to purchase any.

In every treatment village, four such information sessions were held to ensure that households were well-informed and in the best position to make the decision to purchase the insurance. Apart from GUK membership, there were no restrictions on who could attend a given information session, so those who had previously attended one session could attend subsequent sessions in order to address any questions or to purchase the insurance. Indeed, given the high participation rates throughout, it is clear that many GUK members attended all of these information sessions.

[11] Individuals were not notified whether they would receive the rebate during the lean season or at the end of the season prior to making the decision to purchase insurance, so it is not possible that this could have affected insurance demand.

Table 3: Distribution of discounts and rebates among treatment villages

Level of discount/ rebate (percent)	Number of villages in treatment group		
	Discount	Rebate	Total
10	1	1	2
20	1	1	2
30	1	1	2
40	1	1	2
45	1	1	2
50	1	1	2
55	1	1	2
60	2	2	4
65	3	3	6
70	4	4	8
75	5	5	10
80	3	3	6
85	1	1	2
90	6	6	12
Total	30	30	60

Source: Authors.

3.4 Weather realizations and index insurance performance

Based on rainfall measurements at the three *upazila* Agricultural Extension Offices, there were severe droughts that occurred in each of the *upazilas* (dry spells exceeding 14 days) during the *aman* 2013 season. Figure 4 plots the cumulative rainfall in the three *upazilas* during the course of the insurance coverage period. Despite the *upazilas* being in relatively close proximity, Figure 4 highlights the extent to which rainfall realizations can vary over space during the insurance coverage period, ranging from 616 mm in Bogra Sadar *upazila* to only 317 mm in Sariakandi *upazila.* In Bogra Sadar *upazila*, there was a 16 day dry spell from September 10 through September 25; in Gabtoli *upazila*, there was a 16 day dry spell from September 13 through September 28; in Sariakandi *upazila*, there was a 14 day dry spell from September 12 through September 25. Since these dry spells met or exceeded the upper threshold specified in the insurance contracts, all policyholders were entitled to a BDT 600 payout per unit of insurance purchased. GUK administrators ensured that all payouts to farmers were distributed within one month of the culmination of the insurance coverage period.

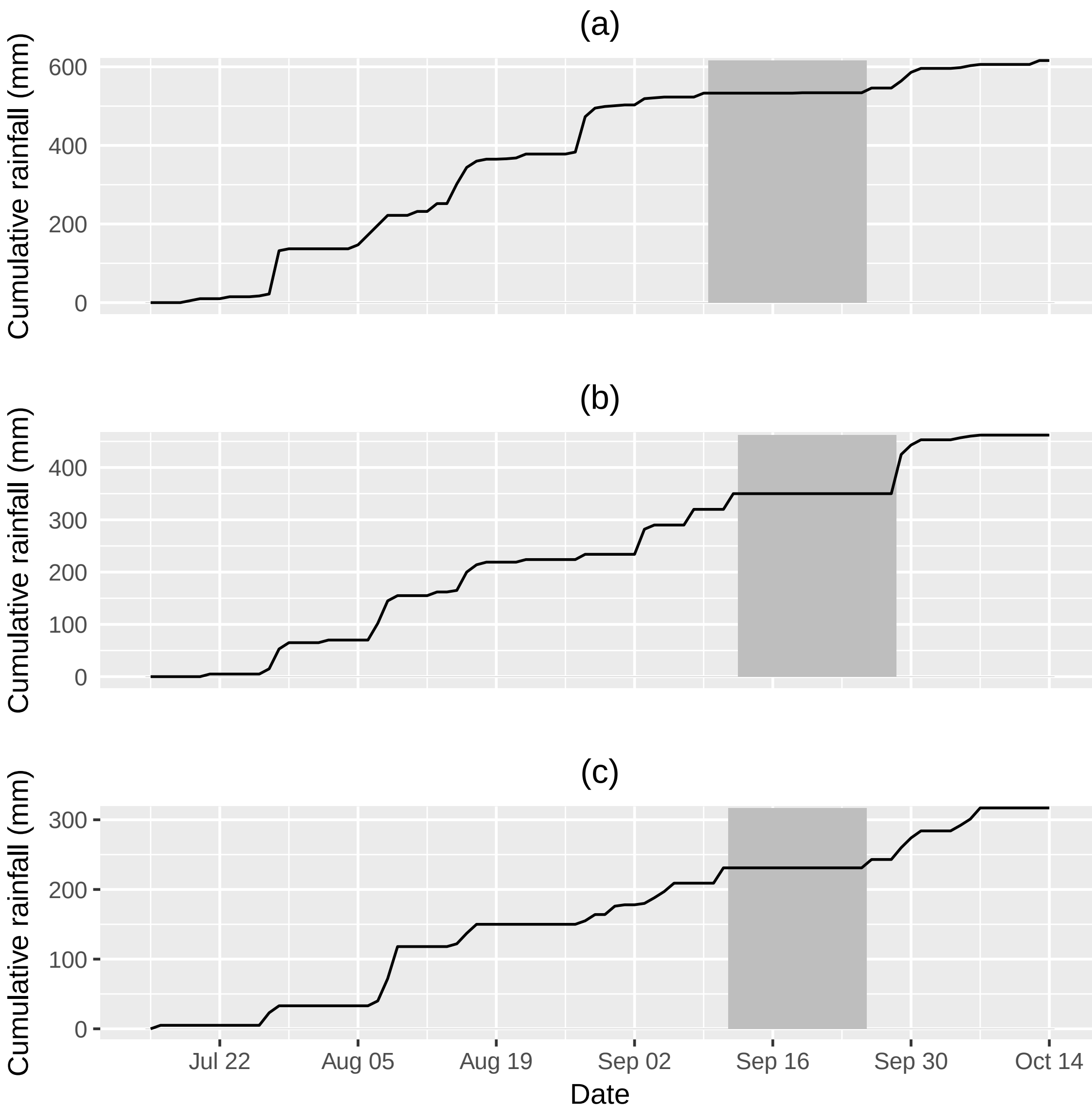

Figure 4: Cumulative rainfall during insurance coverage period (July 15 – October 14, 2013), by *upazila*

Source: Authors; based on data from *upazila* Agricultural Extension Office for (a) Bogra Sadar, (b) Gabtoli, and (c) Sariakandi *upazilas*.
Note: Grey bars indicate the maximum dry spell recorded in each *upazila*.

4 Demand for weather insurance

4.1 Empirical approach

We begin by exploring the determinants of index insurance demand. Here, we focus only on the households from the treatment villages. Our randomization of treatment villages to receiving either a discount or rebate allows us to compare how these two incentives affect households' insurance purchasing decisions, while additional randomization of the level of discount or rebate allows us to assess farmers' sensitivity to these incentives and, ultimately, the cost of insurance. Since take-up of insurance was very high (89 percent of households in the treatment villages purchased at least one unit of insurance), we focus on how the level and nature of the incentive and other characteristics affect the coverage level (i.e., the number of units) that farmers purchase. Among those farmers that purchased insurance, the average coverage amount was nearly 3 units purchased, though there was a nontrivial number of households who purchased 10 or more units (up to a maximum of 25 units). To put this into perspective, on average farmers purchased insurance to cover roughly 51 percent of their total land area.

We first estimate the following equation to estimate the impact of the discounts and rebates on demand:

$$Y_i = \alpha + \beta L_i + \theta \left(L_i \times R_i \right) + \varepsilon_i \tag{1}$$

where Y_i is the number of insurance units purchased by household i, L_i is the level of the rebate or discount, R_i is a binary variable indicating whether a household received a rebate ($R_i = 1$) or a discount ($R_i = 0$), and ε_i is an idiosyncratic error term.

The literature does not provide a clear prediction of whether θ will be larger or greater than β. In general, the impact of a discount is expected to be larger than the impact of a rebate (i.e. $\theta < \beta$) on account of present bias, greater liquidity constraints at the beginning of the season than at the end of the season, and the uncertainty that may surround whether or not the rebate is paid. Such a finding would be consistent with Epley et al. (2006), who find that people are generally more likely to spend income framed as a gain from a current wealth state (e.g., a discount on the cost of purchase) than income framed as a return to a prior state (e.g., a rebate). An important distinction, however, is that in our case, we are not observing the response of receiving a rebate, but rather the present response to the expectation of a future rebate.

Alternatively, a recent study by Serfilippi et al. (2016) demonstrates how insurance demand can actually increase when a specific type of premium rebate is offered (specifically, one in which the insurance cost is deducted from the indemnity). This rebate changes the insurance proposition from one in which costs are certain and benefits are uncertain to one in which both costs and benefits of insurance as uncertain. By making the costs uncertain, the associated disutility of insurance cost is discounted by a penalty for uncertainty (under discontinuous preferences; see Andreoni and Sprenger, 2010), and such insurance contracts are actually more attractive than more traditional contracts without such rebates. The authors argue that this is consistent with individuals having a strong preference for certainty as demonstrated in the Allais paradox and more recently modeled in Andreoni and Sprenger (2010). We may find that the rebate has heterogeneous effects depending on the degree to which individuals are credit constrained, value the present over the future, value certainty or the degree to which they perceive the benefits of the insurance as uncertain.

To assess whether rebates have heterogeneous effects on insurance demand, we estimate the following equation:

$$Y_i = \alpha + \beta L_i + \theta \left(L_i \times R_i\right) + \sum_{j=1}^{J} \gamma_j x_{ij} + \sum_{k=1}^{K} \phi_k \left(z_{ik} \times R_i\right) + \varepsilon_i \tag{2}$$

where $\mathbf{x}_i = \langle x_{i1}, x_{i2}, ..., x_{iJ} \rangle$ is a vector of household- and farm-level characteristics and $\mathbf{z}_i \subset \mathbf{x}_i = \langle z_{i1}, z_{i2}, ..., z_{iK} \rangle$ is a subset of household-level characteristics (time preferences, sufficiency of cash savings, sensitivity to basis risk and risk aversion) that are used to test for heterogeneous rebate effects, and ε_i is an idiosyncratic error term. The parameter vector $\phi = \langle \phi_1, \phi_2, ..., \phi_K \rangle$ also provides some valuable insight into insurance demand, particularly with respect to dimensions of demand heterogeneity.

4.2 Results

The results of estimating equations (1) and (2) by least squares are shown in Table 4. Not surprising, demand for insurance is price-sensitive, with insurance demand increasing with the level of the associated discount or rebate, and robust to various specifications. These results also suggest that demand for insurance would be almost nil without any sort of incentive. In the most parsimonious specification (column (1)), the results suggest that, on average, there would not be any demand for insurance (i.e., at least a single full unit) unless there was at least a 14 percent discount on the cost of insurance, or a 34 percent rebate. This is consistent with the oft-cited narrative that farmers would not be willing to purchase any form of crop insurance, even if at actuarially fair prices. Even after controlling for household- and farm-level characteristics that could plausibly affect insurance demand (column (2)), we find that, on average, there would not be any demand for insurance without at least a 27 percent discount or a 66 percent rebate.

These results suggests that farmers prefer discounts to rebates. Overall, we observe that farmers being offered an discount on the cost of insurance (averaging roughly 67 percent off the base cost of the insurance policy) purchase roughly 3.7 units of insurance, whereas farmers being offered a rebate (also averaging roughly 67 percent of list price) purchase only about 1.2 units of insurance. For a given incentive level, receiving a rebate instead of a discount results in roughly 59 percent fewer units purchased. The timing of the implicit cost reduction is clearly important in farmers' insurance-purchasing decisions.

We examine whether individuals who are more patient reduce demand less when faced with a rebate instead of a discount. Our estimates of the implicit discount rate among the farmers in our sample from survey responses suggest a substantial discounting of future receipts (on average, a roughly 271 percent annual discount rate). But our econometric results reported here do not support the notion that farmers' preference towards the present influences their demand response to a rebate relative to a discount. Indeed, if there is any evidence of the influence of time preferences on insurance demand, it would suggest that farmers with a higher discount rate would demand more insurance if they were given a rebate rather than a discount, though we note this interaction term (hyperbolic discount rate $\times$ rebate dummy) is not significantly different from zero at conventional

Table 4: Estimates of insurance demand

	(1)	(2)	(3)	(4)	(5)	(6)	
Intercept	−0.878	−2.786*	−2.862*	−2.747*	−2.797*	−2.814*	−2.823*
	(0.830)	(1.521)	(1.525)	(1.502)	(1.519)	(1.548)	(1.535)
Level of incentive	0.070***	0.071***	0.072***	0.072***	0.073***	0.075***	0.079***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.022)
Level of incentive × rebate	−0.041***	−0.042***	−0.045***	−0.046***	−0.047***	−0.050***	−0.059***
	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)	(0.013)	(0.015)
Trust		0.196	0.200	0.196	0.196	0.196	0.199*
		(0.122)	(0.122)	(0.121)	(0.121)	(0.121)	(0.119)
Sufficiency of cash savings		−0.353	−0.336	−0.774	−0.348	−0.359	−0.747
		(0.312)	(0.313)	(0.599)	(0.307)	(0.312)	(0.599)
Partial risk aversion		−0.058**	−0.059**	−0.059**	−0.057**	−0.140**	−0.131**
		(0.028)	(0.028)	(0.028)	(0.028)	(0.058)	(0.058)
Ambiguity averse (=1)		0.340	0.356	0.327	0.339	0.376	0.367
		(0.271)	(0.269)	(0.263)	(0.270)	(0.277)	(0.264)
Hyperbolic discount rate		0.027	−0.014	0.030	0.029	0.026	0.008
		(0.039)	(0.060)	(0.040)	(0.039)	(0.039)	(0.065)
Basis risk sensitivity			−0.103	−0.128	−0.568	−0.098	−0.471
			(0.256)	(0.252)	(0.508)	(0.247)	(0.489)
Hyperbolic discount rate × rebate			0.088				0.047
			(0.055)				(0.062)
Sufficiency of cash savings × rebate				0.851			0.814
				(0.638)			(0.636)
Basis risk sensitivity × rebate					0.864		0.696
					(0.556)		(0.522)
Risk aversion × rebate						0.163**	0.145**
						(0.071)	(0.071)
Household/farm controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1082	1082	1082	1082	1082	1082	1082
R^2	0.213	0.246	0.248	0.249	0.249	0.252	0.257

Source: Authors.
Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors adjusted for clustering at the village level in parentheses. Household/farm controls include household head age, gender, and highest education level, household size, asset holdings (index, constructed by principal components analysis), the length of time the household has been a member of GUK, total land holdings, a binary indicator for whether the household has a savings account at a formal financial institution, a binary indicator for whether the household is a member of an informal savings group, the sufficiency of cash savings, and a binary indicator as to whether the household believes most financial institutions can be trusted.

levels. We also find no evidence that those that are more cash constrained are affected differently by a rebate.

Next, we assess whether rebates may work to counter the uncertainty of future payouts. We examine the effect of sensitivity to basis risk on insurance demand.[12] While the point estimate on the main effect is negative (though insignificant), suggesting that farmers sensitive to basis risk might purchase fewer units than those not especially sensitive to basis risk, the interaction effect between basis risk sensitivity and receiving a rebate is positive, suggesting that receiving a rebate increases insurance demand among those sensitive to basis risk relative to receiving a discount (though again, we note that the p-value on this interaction term is only 0.12).

A similar effect emerges when we look at risk aversion. We see that more risk-averse farmers purchase fewer units than those less sensitive to risk, an effect that is statistically different from zero at the 5 percent level. We test for the presence of an inverse U-shape relationship between insurance demand and risk aversion as predicted in Clarke (2016), but we do not find any evidence of such nonmonotonicity with respect to risk aversion (not shown in Table 4), perhaps on account of the fact that our sample of farmers exhibits quite high levels of risk aversion causing the average coefficient on risk aversion to be negative or on account of high expected contract non-performance. What we do find, however, is that when we interact the partial risk aversion coefficient with the rebate dummy, demand is higher for those receiving a rebate relative to those receiving a discount (for a given level of risk aversion and a given incentive amount), and this effect is also statistically different from zero. For those that are risk-averse or especially sensitive to basis risk, the promise of a rebate may provide assurances that they will have some financial recompense in the future, even if they suffer significant crop losses and are not indemnified by the index insurance product.

[12] Basis risk sensitivity is determined based on responses to two different questions. First, suppose you bought insurance each year for five years. You paid the premium each year and the rains were fine five years in a row, so you did not receive a payout. Would you still be interested in purchasing insurance next year? Second, suppose you purchased insurance this year. The rains failed on your field but were sufficient at the weather station where the index is measured, so you did not receive a payout. Would you still be interested in purchasing insurance next year? If the response to both questions was "No," the farmer is considered sensitive to basis risk and is coded as a 1, with 0 otherwise.

5 Effects of insurance on agricultural intensification

5.1 Empirical approach

We now move to estimating the effects of our index insurance product on agricultural intensification. Specifically, we estimate the effects of insurance on investments in modern agricultural inputs (specifically irrigation, pesticides, fertilizer, hired labor, and purchased seeds) and agricultural production (specifically total land cultivated under rice, total rice harvested, and rice yields) in the primarily rainfed *aman* season. Section 2 highlighted that insurance increases risk averse producers' demand for risk-increasing inputs and reduces demand for risk-reducing inputs (Quiggin, 1992). As such we would expect to see farmers increasing their use of risk-increasing inputs such as fertilizer and improved seeds or inputs that increase the scale at which they farm such as land cultivated and labor hired. We would also expect spending on risk-reducing inputs such as pesticides to fall.

The expected impact of insurance on irrigation expenditure is more nuanced. Irrigation is a risk-reducing technology since it provides an alternative method for managing drought risk: farmers can simply "turn on the tap" during prolonged dry spells or when monsoon rainfall is otherwise deficient. At face value, therefore, we would expect spending on irrigation to fall and had we offered a contract that indemnified farmers on the basis of their yields alone, this may be the case. However, these hypotheses are predicated on decision makers contemplating *production* risk and receiving *production* insurance, when in fact what may be driving decisions is *profit* risk and in this case the insurance provided addresses some cost of production risk. Farmers in Bogra typically purchase groundwater from a tubewell pump owner, and when faced with successive dry days often choose to wait one or two more days to see if their crops will survive without incurring the cost of turning on the tap. By making payouts on successive dry days as well as realized yields, the insurance contract guaranteed farmers that they would receive a payout to cover the increase cost they faced in irrigating their crop during these dry spells. As such, for the insurance contract provided we would expect spending on irrigation to increase.

Although the theory predicts that changes in input use induced by the provision of insurance will increase a producer's overall exposure to high production outcomes and increase average production, it does not guarantee that in any one season production outcomes will be higher. In fact in bad states of the world production outcomes could still be lower as a result of the use of strongly risk-increasing inputs.

As previously described, the insurance was offered immediately prior to the 2013 *aman* season, and the *upazila* Agricultural Extension Offices recorded dry spells lasting at least 14 days in each *upazila*, thereby triggering the insurance payout of BDT 600 per unit of insurance purchased.[13] These payments were made by early December 2013 – around the time when farmers were planting their *boro* crops. The timing of the payouts provided liquidity right around the time that farm households were making investments for the 2013-14 *boro* season. This suggests that there is perhaps some potential that purchasing insurance could directly affect the subsequent agricultural season despite it being outside of the specified insurance coverage period. We thus also examine the impact of insurance on modern agricultural input use and agricultural production in the irrigated *boro* season.

In the ensuing analysis, we present only the intention-to-treat (ITT) effects (i.e., the effect of being randomly allocated to the group being offered insurance, regardless of whether or not the household actually purchases the insurance) rather than the average treatment effect on treated households (i.e., the effect of purchasing insurance if randomly assigned to the group being offered insurance).[14] Given the high take-up rates in the present study, reliance on the ITT estimates does not result in significantly attenuated estimates of average treatment effects. Furthermore, such estimates provide broad insight on the potential impact of an insurance program that is introduced at scale.

In the vast majority of applications, treatment effects on economic outcomes are estimated using a difference-in-differences estimator that is essentially a generalization of an analysis of variance (ANOVA) of change. It has been shown that, when autocorrelation in the outcomes of interest is

[13] While the insurance itself was not tied to actual on-farm production, each unit of insurance was meant to provide insurance coverage for an area up to 10 decimals (0.1 acres).

[14] Since the actual receipt of treatment is endogenous (due to households making the decision to purchase insurance), the ITT effect is a biased estimator for the average treatment effect among households that actually purchase insurance. Assuming the correlation between purchasing insurance and agricultural intensification is positive, ITT effects will be downwardly biased, with the magnitude of the bias a function of the proportion of those randomly assigned to be offered insurance making the decision to actually purchase coverage.

low, there are significant gains in statistical power from employing alternative empirical approaches (e.g., see Frison and Pocock, 1992; McKenzie, 2012; Van Breukelen, 2006). One particular estimator that increases statistical power simply by controlling for baseline values of the outcome variable is the analysis of covariance (ANCOVA) estimator (McKenzie, 2012):

$$\delta_{ANCOVA} = \left(\bar{Y}_1^T - \bar{Y}_1^C\right) - \hat{\beta}\left(\bar{Y}_0^T - \bar{Y}_0^C\right) \tag{3}$$

where $\bar{Y}_j^i$ is the mean outcome variable in the treatment ($i = T$) and comparison ($i = C$) groups at the study baseline ($j = 0$) and endline ($j = 1$); $\hat{\beta}$ captures the effect of differences in the pre-intervention levels of the group means for the outcome variable; and δ_{ANCOVA} is the ANCOVA estimate of the effect of random assignment to the treatment group.[15] As Van Breukelen (2006) has noted, $\hat{\beta}$ is a function of both the within-group variance as well as correlations in the pre- and post-intervention values of the outcomes. This equation can be operationalized using least squares by estimating the regression equation

$$y_{i1} = \alpha + \beta y_{i0} + \delta T_i + \mathbf{x}_{i0}^{'}\gamma + \varepsilon_i \tag{4}$$

where, in this equation, y_{i1} and y_{i0} are the endline and baseline levels of the outcome of interest, respectively; T_i is the binary treatment indicator; x_{i0} is a vector of covariates to control for baseline imbalance; and ε_i is an idiosyncratic error term. The α, β, δ, and γ terms are parameters to be estimated. Specifically, δ is an estimate of the impact of the insurance treatment on the outcome variable. Given that exposure to the information and insurance treatments will be similar among GUK members in a particular village, we relax the assumption that error terms are independently and identically distributed, but rather allow for error terms to be independent across villages but correlated within villages. We estimate equation (4) by least squares to arrive at estimates of the ITT effects of our insurance product on the aforementioned indicators of agricultural intensification.

[15] Note that this is different from the classical difference-in-differences estimator, which can be written as $\delta_{DD} = \left(\bar{Y}_1^T - \bar{Y}_1^C\right) - \left(\bar{Y}_0^T - \bar{Y}_0^C\right)$.

5.2 Results

Estimated impacts for the 2013 *aman* season are reported in Table 5, while estimated impacts for the 2013-14 *boro* season are reported in Table 6.[16] Focusing first on the risk mitigation effects during the *aman* season (Table 5), we find that farmers participating in the treatment spent roughly BDT 1400 more on agricultural inputs than did farmers in the comparison group, representing a nearly 16 percent increase over comparison farmers. This increase in input expenditures is not, however, distributed evenly over all inputs. We find that being offered index insurance results in a BDT 250 increase in irrigation expenditures (a nearly 30 percent increase over comparison farmers), a roughly BDT 610 increase in fertilizer expenditures (an almost 20 percent increase over comparison farmers), and a roughly BDT 70 increase in pesticide expenditures (an almost 20 percent increase over comparison farmers). The increased use of fertilizers is consistent with theoretical predictions that risk management induces investments in higher-risk, higher-returning activities, with unambiguous predictions regarding strongly risk-increasing inputs like fertilizer. Fertilizer has the potential to substantially increase yields, but because fertilizer is expensive and there is the potential for significant crop losses under adverse conditions, farmers are often reluctant to invest in applying chemical fertilizers in an environment of unmanaged risk. This finding that insurance increases fertilizer application (or, more accurately, expenditures on fertilizers) is consistent with other research, both theoretical as well as empirical (e.g., Quiggin, 1992; Alderman and Haque, 2007; Karlan et al., 2014).

The increase in irrigation costs is also consistent with theory given that the insurance contract offered protection against this cost of production when many successive dry days were experienced, as was the case in the 2013 *aman*. This result highlights how insurance provided to mitigate the costs associated with managing shocks can encourage households to take appropriate actions to

[16] In the regressions summarized in Tables 5 and 6, we treat total agricultural expenditures and expenditures on irrigation, pesticides, fertilizer, labor, and seeds as independent outcomes, with each independent outcome associated with a unique hypothesis test. In reality, since agricultural inputs are often complementary, our estimation strategy could permit free correlation in error terms across expenditure impact regressions. This could be accomplished by estimating the expenditure impact regressions simultaneously as a 'seemingly unrelated regression' (SUR). While not reported here, we have indeed estimated such relationships, and due to the positive correlations between error terms among these different expenditure categories, we have found both larger and more statistically significant impacts in both *aman* and *boro* seasons. The estimated effects reported here should, therefore, be treated as conservative estimates of the impact of insurance on input expenditures.

Table 5: Least squares estimates of intention-to-treat impacts of index insurance on agricultural intensification and rice production (*aman* season)

	Agricultural input expenditures during *aman* season (BDT)						Land cultivated with rice (decimals)	Quantity rice harvested (kg)	Rice yield (kg/decimal)
	Irrigation	Pesticides	Fertilizer	Hired labor	Purchased seeds	Total			
Baseline level of outcome variable	0.202***	0.397***	0.550***	0.618***	0.078**	1.192***	0.490***	0.393***	0.166***
	(0.052)	(0.094)	(0.121)	(0.150)	(0.036)	(0.223)	(0.062)	(0.071)	(0.035)
Treatment indicator	253.755**	66.219	611.064***	167.383	116.899	1399.994*	−1.214	−60.290	−1.167
	(111.062)	(41.580)	(235.417)	(391.913)	(95.735)	(787.132)	(3.903)	(76.597)	(0.724)
Number of observations	1818	1818	1818	1818	1818	1818	1818	1818	1818
R^2	0.161	0.245	0.324	0.204	0.048	0.365	0.441	0.391	0.038
Mean for comparison group	990.263	357.283	2611.473	2805.440	443.806	8857.426	52.258	885.123	14.671

Source: Authors.

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors adjusted for clustering at the village level in parentheses. Each regression controls for household and agricultural characteristics for which there was an imbalance at baseline between treatment and comparison groups.

Table 6: Least squares estimates of intention-to-treat impacts of index insurance on agricultural intensification and rice production (*boro* season)

	Agricultural input expenditures during *boro* season (BDT)						Land cultivated with rice (decimals)	Quantity rice harvested (kg)	Rice yield (kg/decimal)
	Irrigation	Pesticides	Fertilizer	Hired labor	Purchased seeds	Total			
Baseline level of outcome variable	0.436***	0.078**	0.318***	0.442***	0.053**	0.538***	0.680***	0.687***	0.176***
	(0.050)	(0.038)	(0.051)	(0.070)	(0.024)	(0.050)	(0.066)	(0.072)	(0.034)
Treatment indicator	161.320	47.300	288.357	344.639	116.692*	995.170	4.328*	125.641*	0.359
	(190.657)	(38.207)	(187.719)	(338.718)	(59.869)	(688.951)	(2.630)	(64.349)	(0.436)
Number of observations	1818	1818	1818	1818	1818	1818	1818	1818	1818
R^2	0.222	0.172	0.391	0.371	0.069	0.474	0.481	0.602	0.037
Mean for comparison group	3178.928	437.112	3664.405	3779.840	424.121	13205.118	68.109	1536.906	22.373

Source: Authors.

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors adjusted for clustering at the village level in parentheses. Each regression controls for household and agricultural characteristics for which there was an imbalance at baseline between treatment and comparison groups.

reduce the impact of weather shock on income.

The estimated effect of insurance on increasing pesticide expenditures is positive as well, though only marginally significant (p-value of 0.11). This effect could be considered surprising, since theory would predict expenditures on risk-reducing inputs such as pesticides to decline with insurance. However, given that this is an index insurance product, this is perhaps not as counterintuitive as it appears at first glance. Although the yield risk posed by pests is covered in the average area yield index, farmers will only receive payouts if average yields significantly impacted (whether by pests or otherwise), not if just his or her plot is affected. Furthermore, the area yield measurements would only be considered if neither of the dry-day thresholds were triggered. Increasing expenditures on pesticides helps to reduce some of the risks and associated costs of insurance contract nonperformance by minimizing farmers' exposure to risks not covered by the insurance contract. It could also be the case that attendance in the training session and the purchase of insurance made the issue of managing risks more salient to farmers thereby encouraging them to apply pesticides when needed. We note, however, that any increase in pesticide expenditures is relative to an extremely low base. At baseline, pesticide expenditures accounted for only 4.4 percent of total *aman* season agricultural expenditures. Despite the 20 percent increase in pesticide expenditures relative to farmers in the comparison group, the share of pesticide expenditures in total *aman* season agricultural expenditures among insured households actually declined, dropping to only 4.2 percent of total agricultural expenditures.

While we observe positive estimated effects of insurance on expenditures for hired labor and purchased seeds, the estimated effects are not statistically different from zero at conventional levels (p-values of 0.67 and 0.22, respectively). No positive impact on cultivated area is observed. Additionally, despite the increased expenditures on irrigation, pesticides, and fertilizers, we do not observe any concomitant increase in yields, or total production. Increased spending on inputs does not guarantee higher yields in each state of nature, only higher yields on average. One likely reason for this somewhat surprising non-result is that there were prolonged dry spells that occurred in each of the *upazilas* during the 2013 *aman* season, and these dry spells all occurred in mid- to late-September, during which many longer-duration *aman* varieties would be reaching their reproductive stages. While increased expenditures on irrigation would ameliorate some of the effects of deficient rainfall during this time, there are also potentially offsetting effects of burn damage brought about by increased use of chemical fertilizers. We do not have sufficient information on the timings of these various irrigation and fertilizer applications, so we cannot definitively trace out a causal pathway. Rather, we simply note the potential for these countervailing forces, and the ultimate result that, despite the increased expenditures on inputs, the dry spell likely resulted in yield losses which could have been higher for those using risk-increasing inputs.

Table 6 reports the least squares ITT impacts on agricultural intensification during the *boro* season. As with impacts during *aman* season, we find that being exposed to our index insurance product leads farmers to spend more on agricultural inputs than those who were never exposed to our insurance product; in the case of *boro* rice, nearly BDT 995 (7.5 percent) more than farmers in the comparison group (though this estimated effect on total agricultural expenditues is not statistically significant at conventional levels, with a p-value of 0.15). Again, as before, the increased expenditures are not spread uniformly over the different inputs. In fact, the only statistically significant effect of insurance exposure on input use is an increase in seed expenditures.[17] Exposure to the insurance product increases seed expenditures by nearly BDT 117, representing a roughly 28 percent increase in seed expenditures over farmers in the comparison group. Since the insurance product was marketed prior to and covered the *aman* season, we cannot attribute these effects to risk management effects (since *boro* season risks remain uninsured). However, because the insurance payments were made following the *aman* harvest and just prior to the initiation of the *boro* season, these income effects likely arise due to insured farmers realizing increased liquidity. Since we do not have data on how insured farmers' might have behaved with respect to their *boro* input expenditures in the absence of an insurance payout (which, consequently, means in the absence of a measured drought or crop loss during the *aman* season), we cannot say for certain that this effect would only hold after receipt of an insurance payout. If indeed the increased seed expenditures during *boro* arose due to an income effect, then perhaps there would be no reason to expect this sort of response in the absence of an insurance payout, especially since there was not a discernible effect on *aman*

[17]In addition to this effect on seed expenditures, there is a marginally significant positive effect on fertilizer expenditures (p-value of 0.12).

production in Table 5.[18]

The increased expenditures on seeds during the *boro* season is important for several reasons. First, while the grains from most rice varieties can be stored and used for seeds in subsequent generations, such seed saving necessarily limits farmers' access to technological improvements (e.g., higher yields, biotic and abiotic stress tolerance, etc.) embodied in newer varieties (Spielman et al., 2013). Second, saved seeds tend to suffer from physical and genetic deterioration over time. For example, saved seeds typically have lower germination rates than do new seeds, so farmers would typically need to sow at higher seeding rates to acheive comparable levels of crop emergence as they would with new seeds. Additionally, those sprouts that do emerge often become less productive from one generation to the next. Third, the increased seed expenditures may signal farmers' transition from inbred rice varieties to rice hybrids, which are almost exclusively cultivated during the dry winter season in Bangladesh. While hybrids are considerably more expensive than inbred varieties (even high-yielding varieties) and must be purchased anew every season, they also confer significantly higher yields and have greater genetic uniformity and vigor, which enables farmers to sow at much lower seeding rates (Spielman et al., 2016). Additionally, since hybrids are almost exclusively developed by the private sector, there is greater potential for technological innovations in hybrids than in varieties developed by the public sector. While we do not know for certain that the increased seed expenditures translated into hybrids, the relative magnitude of the increase in seed expenditures makes such a scenario plausible.

We find a positive and statistically significant effect of insurance on both the area cultivated under *boro* and the subsequent rice harvest, though based on our analyses we are unable to detect an increase in productivity. We are somewhat cautious about being too enthusiastic about the mea-

[18]It is possible that risk management during the *aman* season might also produce an income effect that results in increased seed expenditures during the *boro* season, regardless of whether an insurance payout was received. Admittedly we do not have an adequate counterfactual at our disposal with which to test this hypothesis, so this remains largely conjectural. Suppose there was *not* a drought during the *aman* season. Because we observe higher expenditures on modern inputs among insured farmers (vis-á-vis farmers in the comparison group) as a result of risk management (independent of the resultant state of nature), and because we would expect strictly positive marginal productivities for all inputs during *aman* production under such conditions, total *aman* output for insured farmers should exceed that of uninsured farmers. This, in turn, could produce a similar income effect as the insurance payment and induce increased expenditures on fertilizers during the *boro* season. The relative magnitudes are impossible to quantify in the absence of a proper counterfactual, but it seems at least plausible that the income effects and increased input expenditures during the *boro* season could at least indirectly result from the risk management effects that arise during the *aman* season.

sured effects on cultivated area. Previous research (e.g., Abate et al., 2015) has found that farmers are remarkably skilled at estimating their total production, yet tend to systematically measure plot sizes with error, such as rounding off their area estimation and making errors in converting from local units to a standard areal unit such as an acre. Farms in Bangladesh typically consist of several very small and fragmented plots, so it is easy to see how rounding errors can be compounded as the number of plots increases. Since yield data are constructed based on self-reported production and area data, it is plausible that the lack of a significant effect on yields is due to errors in measuring cultivated area. These errors in measuring plot sizes would then, by definition, translate into errors in yield measurements. Specifically, if area measurements are systematically biased upwards, then for a given production level, the computed yield would be downwardly biased. Measurements of total production are less prone to such systematic measurement errors and may therefore serve as more reliable estimates of the impacts of the increased seed expenditures on production. Given the significant effect that the insurance has on increasing seed purchases, and the presumable driving force behind such purchases being a quest for higher yields, it seems plausible that the increase in total production is attributable to increases along the intensive – rather than extensive – margin.

6 Concluding remarks

In this paper we present early results from a weather-based index insurance program in rural Bangladesh. The pilot provided treated farmers with easily verifiable and transparent insurance coverage against specified dry spells during the *aman* season, backed by coverage assessed on an area-yield basis. Our empirical analysis focuses on both the determinants of insurance demand as well as the subsequent effects of insurance on agricultural intensification and rice production. Our results provide valuable insight into the potential viability of insurance markets in rural Bangladesh, as well as the potential benefits that such an insurance product might provide, both in terms of risk management as well as increased income.

In our analysis of insurance demand, results are consistent with much of the empirical literature demonstrating that demand for insurance is price-sensitive. In the absence of financial incentives such as discounts or rebates, our results suggest there would be essentially no demand for our insurance product, even at market prices below actuarially fair levels. The nature of the incentive also plays a role in stimulating demand. Up-front discounts on the cost of insurance are much more successful at stimulating insurance take-up compared to rebates, which necessarily involve a delay in the receipt of the monetary inducement. This not only affects whether individuals decide to purchase insurance, but also the coverage level that they purchase. On average, individuals receiving a discount purchase roughly 3.7 units of insurance, while those offered a rebate purchase only 1.2 units of insurance. Interestingly, demand among some farmers in our sample (particularly very risk-averse farmers and those that are especially sensitive to the presence of basis risk) responded more favourably to the rebate, perhaps because the rebate helps to offset the costs of contract non-performance (i.e., basis risk), since it provides the assurance of some financial inflow in the future even if the insurance contract never pays out.

In our analysis on the impacts of insurance on agricultural intensification and rice production, we find evidence of both ex ante as well as ex post impacts. The ex ante impacts, which we consider as pure risk management effects, translate into significantly higher expenditures on several agricultural inputs during the *aman* rice growing season. Specifically, we find that insurance leads to significantly higher expenditures on irrigation and fertilizer, with a marginally higher impact on pesticide expenditures. At first glance, the effects on irrigation and pesticide expenditures are contrary to theoretical predictions, given that both inputs reduce production risk. However, the insurance contract offered helped cover the costs of irrigation when they were being used to combat successive dry days, and as such the contract increased expenditure on this risk-mitigating expenditure. The results highlight that appropriately designed insurance contracts can encourage beneficial risk-mitigation behavior. Additionally, the effects on pesticide expenditures – which, notably, are relatively small as a share of overall agricultural expenditures – may arise due to the nature of index insurance. Farmers increase expenditures on pesticides and thus reduce the risks and associated costs of basis risk.

During the *boro* season, insurance results in increased expenditures on seeds and, consequently, higher rice production. Since the insurance contract was designed to manage only *aman* season risks, this impact cannot be considered a risk management effect. Rather, due to the timing of the insurance payouts (following the *aman* harvest and prior to *boro* land preparation), this ex post effect reflects the increased income or liquidity that insured households reap, in this case as a result of the insurance payout. Given insufficient exogenous variation in insurance payout receipts (since all insured farmers receive a payout), we are unable to say with any degree of certainty that this effect would only be present following an insurance payout (which, in turn, occurs only in the event of a measured drought at the agricultural extension office or through crop-cutting exercises). This causal pathway seems plausible, though we also suggest that such an income effect could occur even in the absence of an insurance payout, for example due to increased farm profits from *aman* production (e.g., since the ex ante effects of insurance increase agricultural intensification during the *aman* season). Parsing out this effect remains a task for future research.

The results highlighted here come from a single study spanning two agricultural seasons. Furthermore, these results are largely compelling due to the very high take-up rates, which were induced by very high incentives on favorably-priced index insurance. It remains to be seen whether such an index insurance program is sustainable, whether positive experiences with insurance programs can stimulate demand even without incentives, or, ultimately, whether the ex ante and ex post impacts of insurance would be realized without the sizable incentives. The large number of related studies that are ongoing in other countries should provide more insight into these unanswered questions.

References

Abate, G. T., A. de Brauw, N. Minot, and T. Bernard (2015). The impact of the use of new technologies on farmers' wheat yield in Ethiopia: Evidence from a randomized controlled trial. Discussion Paper 01462, International Food Policy Research Institute, Washington, DC.

Alderman, H. and T. Haque (2007). *Insurance against covariate shocks.* Washington, DC: The World Bank.

Andreoni, J. and C. Sprenger (2010). Certain and uncertain utility: The Allais Paradox and five decision theory phenomena. Mimeo.

Barnett, B. J., C. B. Barrett, and J. R. Skees (2008). Poverty traps and index-based risk transfer products. *World Development 36*(10), 1766–1785.

Barnett, B. J. and O. Mahul (2007). Weather index insurance for agriculture and rural areas in lower-income countries. *American Journal of Agricultural Economics 89*(5), 1241–1247.

Berhane, G., R. V. Hill, S. Dercon, and A. Seyoum Tafesse (2014). The impact of insurance on agricultural investment: Evidence from Ethiopia. Mimeo.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics 62*(3), 395–407.

Binswanger-Mkhize, H. P. (2012). Is there too much hype about index-based agricultural insurance? *Journal of Development Studies 48*(2), 187–200.

Cai, J. (2016). The impact of insurance provision on households' production and financial decisions. *American Economic Journal: Economic Policy 8*(2), 44–88.

Carter, M. R., L. Cheng, and A. Sarris (2016). Where and how index insurance can boost the adoption of improved agricultural technologies. *Journal of Development Economics 118*, 59–71.

Carter, M. R., A. de Janvry, E. Sadoulet, and A. Sarris (2014). Index-based weather insurance for developing countries: A review of evidence and a set of propositions for up-scaling. Technical report, FERDI/Agence Francaise de Development, Paris.

Clarke, D., F. de Nicola, R. V. Hill, N. Kumar, and P. Mehta (2015). A chat about insurance: Experimental results from rural Bangladesh. *Applied Economic Perspectives and Policy 37*(3), 477–501.

Clarke, D. J. (2011). *Insurance design for developing countries.* D.Phil dissertation, Balior College, University of Oxford.

Clarke, D. J. (2016). A theory of rational demand for index insurance. *American Economic Journal: Microeconomics 8*(1), 283–306.

Cole, S., X. Giné, J. Tobacman, P. Topalova, R. Townsend, and J. Vickery (2013). Barriers to household risk management: Evidence from India. *American Economic Journal: Applied Economics 5*(1), 104–135.

Cole, S., X. Giné, and J. Vickery (2013). How does risk management influence production decisions? Evidence from a field experiment. Policy Research Working Paper No. 6546, World Bank, Washington, DC.

Delavallade, C., F. Dizon, R. V. Hill, and J. P. Petraud (2015). Managing Risk with Insurance and Savings: Experimental Evidence for Male and Female Farm Managers in the West Africa. Discussion Paper 01426, International Food Policy Research Institute.

Elabed, G. and M. R. Carter (2015). Ex-ante impacts of agricultural insurance: Evidence from a field experiment in Mali. Unpublished manuscript.

Epley, N., D. Mak, and L. C. Idson (2006). Bonus or rebate?: The impact of income framing on spending and saving. *Journal of Behavioral Decision Making 19*(3), 213–227.

Frison, L. and S. L. Pocock (1992). Repeated measures in clinical trials: Analysis using mean summary statistics and its implications for design. *Statistics in Medicine 11*, 1685–1704.

Giné, X., R. Townsend, and J. Vickery (2008). Patterns of rainfall insurance participation in rural India. *World Bank Economic Review 22*(3), 539–566.

Giné, X. and D. Yang (2009). Insurance, credit, and technology adoption: Field experimental evidence from Malawi. *Journal of Development Economics 89*(1), 1–11.

Hazell, P., J. Anderson, N. Balzer, A. Hastrup Clemensen, U. Hess, and F. Rispoli (2010). *The potential for scale and sustainability in weather index insurance for agriculture and rural livelihoods.* Rome: World Food Programme.

Hazell, P., C. Pomareda, and A. Valdés (Eds.) (1986). *Crop insurance for agricultural development.* Baltimore: Johns Hopkins University Press.

Hazell, P. B. (1992). The appropriate role of agricultural insurance in developing countries. *Journal of International Development 4*(6), 567–581.

Hill, R. V., J. Hoddinott, and N. Kumar (2013). Adoption of weather-index insurance: Learning from willingness to pay among a panel of households in rural Ethiopia. *Agricultural Economics 44*(4-5), 385–398.

Hill, R. V., M. Robles, and F. Ceballos (2016). Demand for a simple weather insurance product in India: Theory and evidence. *American Journal of Agricultural Economics 98*(4), 1250–1270.

Hill, R. V. and A. Viceisza (2012). An experiment on the impact of weather shocks and insurance on risky investment. *Experimental Economics 15*(2), 341–371.

Janzen, S. A. and M. R. Carter (2013). After the drought: The impact of microinsurance on consumption smoothing and asset protection. Working Paper 19702, National Bureau of Economic Research, Cambridge, MA.

Karlan, D. and J. Morduch (2009). Access to Finance. In D. Rodrik and M. Rosenzweig (Eds.), *Handbook of Development Economics*, Volume 5, pp. 4704–4784. Amsterdam: Elsevier.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2014). Agricultural decions after relaxing credit and risk constraints. *Quarterly Journal of Economics 129*(2), 597–652.

McIntosh, C., A. Sarris, and F. Papadopoulos (2013). Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia. *Agricultural Economics 44*(4-5), 399–417.

McKenzie, D. (2012). Beyond baseline and follow-up: The case for more T in experiments. *Journal of Economic Development 99*, 210–221.

Miranda, M. J. (1991). Area-yield crop insurance reconsidered. *American Journal of Agricultural Economics 73*(2), 233–242.

Mobarak, A. M. and M. R. Rosenzweig (2012). Selling formal insurance to the informally insured. Unpublished manuscript.

Mobarak, A. M. and M. R. Rosenzweig (2013). Informal risk sharing, index insurance, and risk taking in developing countries. *American Economic Revierw 103*(3), 375–380.

Morduch, J. (2006). Microinsurance: The next revolution? In A. Bannerjee, R. Benabou, and D. Mookherjee (Eds.), *Understanding poverty*, pp. 337–357. New York: Oxford University Press.

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

Quiggin, J. (1992). Some observations on insurance, bankruptcy and input demand. *Journal of Economic Behavior and Organization 18*, 101–110.

Ramamasy, S. and S. Baas (2007). *Climate variability and change: Adaptation to drought in Bangladesh.* Rome: FAO.

Rosenzweig, M. R. and H. P. Binswanger (1993). Wealth, weather risk and the composition and profitability of agricutlural investments. *Economic Journal 103*(416), 56–78.

Sandmo, A. (1971). The competitive firm under output price uncertainty. *American Economic Review 61*(1), 65–73.

Serfilippi, E., M. Carter, and C. Guirkinger (2016). Certain and uncertain utility and insurance demand: Results from a framed field experiment in Burkina Faso. Mimeo.

Skees, J. R. (2008). Innovations in index insurance for the poor in lower income countries. *Agricultural and Resource Economics Review 37*(1), 1–15.

Spielman, D. J., D. E. Kolady, and P. S. Ward (2013). The prospects for hybrid rice in India. *Food Security 5*, 651–665.

Spielman, D. J., P. S. Ward, D. E. Kolady, and H. Ar-Rashid (2016). Public incentives, private investment, and outlooks for hybrid rice in Bangladesh and India. *Applied Economics and Policy Perspectives Forthcoming*.

Van Breukelen, G. J. (2006). ANCOVA versus change from baseline had more power in randomized studies and more bias in nonrandomized studies. *Journal of Clinical Epidemiology 59*, 920–925.

Ward, P. S. and S. Makhija (2016). New modalities for managing drought risk in rainfed agriculture: Evidence from a discrete choice experiment in Odisha, India. Discussion Paper 01563, International Food Policy Research Institute, Washington, DC.