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Insuring against drought: Evidence on agricultural intensification and demand for index insurance 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 fairly price elastic, with discounts significantly more successful in stimulating demand than rebates. Purchasing 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 modern agricultural inputs during the *aman* rice growing season, particularly for productivity-enhancing inputs such as fertilizers, irrigation, and pesticides. The income effects lead to increased seed and fertilizer expenditures during the *boro* rice growing season.

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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 hybrid 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 with 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 is a hybrid index insurance product that provides risk management against both production and profit risks. The product 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 hybrid 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 only implicitly 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 transfers income from high-income states of the world to low-income states of the world, increasing utility for risk-averse individuals. Insurance is also expected to increase average incomes for farm households by impacting production behavior. There has long been 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, production risk may arguably have a greater impact on production decisions in the agricultural sector, and is almost certainly the most salient source of risk faced by smallholder farmers in developing countries. In studying the role of production risk in conditioning production decisions, Pope and Kramer (1979); Quiggin (1992) and Ramaswami (1992) have demonstrated that factor demands depend crucially on the risk preferences of the producer and the risk profile of the input (i.e., whether the input is risk-increasing, risk-reducing, or risk-neutral). Quiggin (1992) demonstrates how insurance can, assuming the inputs are not costless, increase the overall exposure to high production outcomes for risk averse producers.[1]

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 al-

[1]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.

lows 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).

Despite these benefits, however, index-based insurance has a considerable disadvantage. 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 risk that a farmer may incur a large loss and still not receive any payment from the insurance contract 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).[2] 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. 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. In the presence of basis risk the traditional theoretical predictions regarding the relationship between risk aversion and insurance demand also no longer hold, since the product itself is now risky. Instead, 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). Hill et al. (2016), for example, find that demand for index insurance is inverse U-shaped in risk aversion, and others have documented a negative relationship between risk aversion and demand (Giné et al., 2008).

Indeed, across various countries and contexts, uptake of index insurance has been low even

[2] 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.

when offered at actuarially-favorable rates. In Ghana, Karlan et al. (2014) find a price elasticity of roughly -2.[3] Cole et al. (2013) estimate a price elasticity of demand between -1.04 and -1.16 in Andhra Pradesh. Other studies find more moderate price elasticities: Hill et al. (2016) estimate the price elasticity of insurance demand to be -0.58, while Mobarak and Rosenzweig (2012) find the price elasticity to be -0.44.

The emerging evidence around many index insurance products is that subsidies are often required – at least the short run – to stimulate demand (J-PAL, CEGA, and ATAI, 2016). These subsidies can take various forms, but we focus on discounts and rebates. Discounts and rebates primarily differ in the timing with which the benefits are realized, but they can also interact differently with idiosyncratic behavioral preferences and can have different implications for insurers' business models. In typical index insurance contracts the premium is paid by the insured prior to the start of the coverage period for a promise of later payment conditional upon some adverse event being realized. This can cause liquidity constraints, low trust in the insurance provider, and present-bias to constrain demand (e.g., Karlan et al., 2014). In this context discounts can be particularly effective and we would expect them to be more effective than rebates. This 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). Discounts might be especially successful in addressing liquidity constraints in the context of smallholder agriculture, since the decision to purchase insurance is often concurrent with decisions regarding agricultural production (e.g., investments in agricultural inputs). For insurers, providing discounts may result in increased insurance sales, but at the expense of deteriorating revenues relative to value-at-risk, which may constrain their ability to reinsure. Providing subsidies in the form of rebates would ameliorate some of these constraints, but likely at the expense of lower insurance demand.

There is both theoretical and empirical evidence that behavioral preferences may lead some individuals to respond favorably to rebates. For farmers that are especially risk averse or who are

[3]This study is a prominent counterexample to the widely observed phenomenon of low demand. 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. The price elasticity is estimated as the mid-point of the arc elasticity between the actuarially-fair insurance and the market price insurance.

susceptible to basis risk, having a promise of future remuneration even in the event of contract nonperformance may actually increase the value of the insurance contract relative to the costs of basis risk. Furthermore, 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), particularly when there is significant uncertainty about the payout as a result of basis risk. In essence, the 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 are 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 become more attractive than more traditional contracts without such rebates.

In cases where sufficient uptake of insurance has occurred, impacts of index-insurance have largely been positive (Carter et al., 2014). Janzen and Carter (2013) find that index insurance positively affects pastoral farm households in Kenya 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. 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. Insured farmers cultivated nearly an acre more land and spent nearly 14 percent more on land preparation costs while simultaneously increasing expenditures on modern inputs (mostly fertilizers) by nearly 24 percent. In Burkina Faso, Senegal and Ethiopia farmers who had weather index insurance purchased more fertilizer (Delavallade et al., 2015; Berhane et al., 2014). In Andhra Pradesh and Tamil Nadu, India, two separate RCTs find that insurance causes farmers to invest in higher-return, rainfall-sensitive cash crops (Cole et al., 2013; Mobarak and Rosenzweig, 2012).

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 Table 1).

Table 1 approximately here

Three *upazilas* (subdistricts) within Bogra were selected on the basis of proximity to the district meteorological station operated by the Bangladesh Meteorological Department (Figure 1). 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. 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 2 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 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. In total, households cultivated 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 (91 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.

Figure 1 approximately here

Table 2 approximately here

[4]While the initial sample consisted of 2,300 agricultural households, with very little attrition between baseline and follow-up, the sample sizes that emerge in Tables 2, 5, 6, and 7 are smaller than the original sample because we focus on those households that cultivated both *aman* and *boro* rice.

[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.

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 salience 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 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 2). 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.[7] The insurance design was informed by extensive formative research. In related

[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.

[7]Results from a telephone survey conducted prior to the follow-up household survey among a randomly selected sample of farmers in treatment villages indicate that roughly 90 percent of farmers access groundwater to supplement rainfall, with the vast majority of those accessing water resourced through a contractual relationship with a local pump owner (less than 10 percent of those interviewed owned their own pump). The nature of the contracts was widely variable, with most farmers paying a fixed amount (either in cash or as a share of their harvest) at the end of the season. Roughly 30-35 percent of those interviewed through this telephone survey reported paying for irrigation on a variable basis, with nearly 2/3 of those paying cash after each operation. Among those paying on a variable basis, most paid roughly BDT 10 per decimal when they irrigated, regardless of the depth or the amount of diesel or

work, Clarke et al. (2015) conducted an insurance demand-elicitation exercise in Bogra in which farmers demonstrated their interest in various types of insurance products by allocating a monetary endowment across various financial instruments. Clarke and co-authors find that insurance demand varies with the prevalence of the risk that it insures, especially for the case of area yield and dry-days insurance. Based on this formative research, the insurance product developed for the present study protects 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.[8] According to the policy specifications, the insured would receive a payout if a long period of successive dry days was recorded at the local weather station *or* if the average area yield in the *upazila* was very low. Table 3 describes these events and how they relate to policy triggers 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 14 days, the policy would pay out BDT 600.[9] On average, this type of dry spell occurs roughly once every decade. If the longest dry spell that occurred was 12 or 13 days in length, the policy holder would receive a payment of BDT 300. This type of dry spell occurs roughly once every five years on average.[10] 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

volume of water used. When we attempted to implement a similar series of questions during the follow-up household interviews, the responses were somewhat contradicotry, with nearly 95 percent of farmers indicating that they a fixed contract, although because of the wording of this question it is not clear they understood the difference between fixed and variable contracts.

[8]For the purposes of this index insurance product, a "dry-day" was any day (midnight to midnight) in which the cumulative rainfall was less than 2 mm.

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

[10]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 predict the levels (i.e., dry spell lengths) associated with the associated return periods (that is, the inverse of the probability that a particular event will occur in any given year.

26 maunds per acre, the policy would pay out BDT 300.[11] 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 roughly one fifth of the rice area cultivated in this season. Households had the option of purchasing multiple units of insurance based on the amount of land they cultivate during the monsoon season, but were only eligible purchase insurance coverage for the amount of land they cultivated, thereby reducing any incentive to view the insurance as a gamble.

Table 3 approximately here

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.

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

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 4 provides the distribution of villages by the level of discount or rebate. 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.

Table 4 approximately here

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.

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 3 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 3 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 3 approximately here

4 Demand for weather insurance

4.1 Empirical approach

We begin by exploring the determinants of index insurance demand. Figure 4 illustrates the patterns of insurance take-up at varying levels of discounts and rebates. 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 the effective cost of insurance, and, ultimately any differential in their price sensitivity depending on the nature of the incentive offered. Since take-up of insurance was very high (88 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 the perspective of coverage area, farmers that purchased insurance on average purchased insurance to cover roughly 83 percent of their total area under *aman* cultivation.

Figure 4 approximately here

We begin by estimating the following linear regression equation to estimate the impact of discounts and rebates on demand:

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

where Q_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. This model assumes that the intercepts under discounts and rebates is the same (e.g., $E[Q_i; R_i = 0, L_i = 0] = E[Q_i; R_i = 1, L_i = 0]$), but allows for the slopes of the demand response curves (β and $\beta + \theta$, respectively) to differ.

So long as $\beta > 0$ and $\beta + \theta > 0$ insurance demand will be increasing in both discounts and rebates. Both theory and empirical evidence would largely support both of these predictions, though there has not yet emerged a consensus as to the relative magnitudes of these incentive response slopes, nor as to whether $\theta > 0$. In general, the impact of a discount is expected to be larger than the impact of a rebate (i.e. $\theta < 0 < \beta$) 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. However, if individuals have discontinuous preferences between certain and uncertain outcomes, this preference for discounts may be moderated Serfilippi et al. (2016). 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:

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

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 5 in columns (1)-(6). Not surprising, demand for insurance is price-sensitive, with insurance demand increasing with the level of the associated discount ($\hat{\beta} > 0$) or rebate ($\hat{\beta} + \hat{\theta} > 0$), and robust to various specifications.[12] Since $\hat{\theta} < 0$, we know that the slope of the demand response to rebates is flatter than the demand response to discounts, though we can reject the null hypothesis that $\hat{\beta} + \hat{\theta} \leq 0$, suggesting that insurance uptake is still increasing in rebate levels despite the preference for discounts. These results also suggest that demand for insurance would be essentially nil without any sort of incentive to encourage take-up due to the statistically insignificant intercept term $\hat{\alpha}$.

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 15 percent discount on the cost of insurance, or a 35 percent rebate.[13] This is consistent with the oft-cited narrative that farmers would not be willing to purchase any form of crop insurance,

[12] Implicitly, our results suggest a price elasticity of insurance demand of -0.65, which is well within the range of other observed elasticity estimates (e.g., Mobarak and Rosenzweig, 2012; Hill et al., 2016; Cole et al., 2013; Karlan et al., 2014).

[13] This assumes that the intercept on the demand response curves for both discounts and rebates is zero, as implied by the statistically insignificant intercept term in column (1), and is calculated as $L_i^* = 1/(\hat{\beta} + \hat{\theta} R_i)$ evaluated both at $R_i = 0$ (discount) and $R_i = 1$ (rebate).

even if at actuarially fair prices. In column (2), we control for a series of household and farm-level characteristics that might plausibly influence insurance take-up (e.g., as suggested by existing literature; see e.g Platteau et al., 2017). The demand responses to the incentive mechanisms is largely robust to the inclusion of these other covariates, and their inclusion does not contribute much to explaining the variation in insurance take-up. Columns (3)-(6) introduce a series of interactions between the binary rebate indicator and a series of behavioral factors and distance to the *upazila* agricultural extension office, which serves as an indicator of susceptibility to basis risk. By and large, the inclusions of these interactions fail to explain much more of the variation in insurance take-up than the more parsimonious specifications, with perhaps the exception of the interaction between the binary rebate indicator and distance to the *upazila* agricultural extension office. As was observed in the more parsimonious model, across all models in columns (2)-(6) we find $\hat{\theta} < 0$, though we reject the null hypothesis that the linear combination $\hat{\beta} + \hat{\theta} \leq 0$.

Table 5 approximately here

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 70 percent off the base cost of the insurance policy) purchase roughly 3.5 units of insurance, whereas farmers being offered a rebate (also averaging roughly 70 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 57 percent fewer units purchased. The timing of the implicit cost reduction is clearly important in farmers' insurance-purchasing decisions.

In column (3), 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 262 percent annual discount rate). We might expect that increasing hyperbolic discount rates would result in a stronger preference for present consumption, which would presumably be higher among those receiving a discount. Interestingly, the results reported here seem to suggest the opposite. Specifically, these results suggest that farmers with a higher discount rate would demand more insurance if they were given a rebate rather than a discount. While this result may not be an empirical regularity, there is a plausible explanation for this result. In attempting to explain why individuals with hyperbolic time preferences would purchase more health insurance than those without such time preferences, Ito and Kono (2010) argue that this phenomenon reflects individuals' use of health insurance as a commitment device that facilitates the 'prepayment' of healthcare expenses, given their awareness of their own self-control problems and inability to save to buffer against future healthcare expenditures. In our particular case, it is apparently not only the insurance itself that acts like a commitment savings vehicle, but the rebate also serves as a promise of a future cash inflow that could serve as deferred consumption for those with a strong preference for the present. We note, however, that these effects become insignificant in models in which risk aversion is also accounted for (e.g., column [6]), perhaps suggesting that time preferences and risk preferences may be conflated, or in the least are highly correlated.

In column (4), we assess whether rebates may work to counter individuals' 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 5), 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. We do find, however, 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 (and who may be 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. In a comprehensive model that controls for the full suite of explanatory models, this interaction effect too becomes statistically insignificant (though the main effect remains statistically significant), again likely due to the conflation of risk preferences and time preferences.

Finally, in column (5), we assess whether rebates may work to counter individuals' susceptibility to basis risk. In the models reported in columns (2)-(6), the estimate for the effect of distance on demand is negative, suggesting that individuals further away from the *upazila* agricultural extension office would purchase fewer units of insurance, likely because they intuit that they are exposed to increased basis risk. When we introduce the interaction term (column [5]), we see that the interaction effect is positive and roughly equivalent in magnitude. This suggests that, while being further away from the *upazila* agricultural extension office (and thus being exposed to a greater susceptibility to basis risk) would reduce index insurance take-up on average, receiving a rebate on the purchase of the insurance would essentially wipe out this effect. In other words, the rebate may compensate farmers for the increased exposure to basis risk and offset the costs associated with basis risk, particularly in states of the world in which they experience losses on their farms and yet are not indemnified by the index insurance product.

The above effects demonstrate some interesting evidence on heterogeneous effects of discounts and rebates in stimulating insurance demand, but should be taken with a degree of caution. These results were predicated on the assumption that the underlying demand response specification was linear in the discount and rebate level, and such a linearity assumption could be exaggerating these effects. In column (7), we report the parametric estimates for the same set of household and farm level characteristics and interactions included in columns (2)-(6), but now with the discount and rebate level effects incorporated as a series of binary variables. In a way, this is similar to a semiparametric regression, but rather than estimating the nonparametric discount and rebate level effects through a local polynomial regression function, they are discretized. This discretized nonparametric relationship is shown in Figure 5. By and large, this figure illustrates that only large discounts seem to stimulate any sizable insurance demand, and they work much better than rebates of an equivalent magnitude. The results in column (7) suggest that much of the variation in insurance take-up that can be explained by observable characteristics is due to the incentives (note the marked increase in R^2 by adopting this more flexible specification), with the behavioral characteristics and exposure to basis risk contributing relatively little explanatory power. While these results may qualify our interpretation of the behavioral influence on insurance demand (as told above), we also note that they may be understating these influences, as explanatory power is absorbed by the discount and rebate levels which are perfectly measured and provide a very clean source of exogenous variation. The behavioral characteristics are measured imperfectly, and we may simply lack the statistical power to precisely measure their effects (we note that all of the signs on the point estimates are retained in moving from column [6] to column [7]).

Figure 5 approximately here

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 expenditures on agricultural inputs such as 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.[14] 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

[14] In reality, land is a factor of production, and thus decisions about the area of land to be cultivated could reasonably be included in a discussion about agricultural input use. In what follows, we differentiate land from the other inputs insomuch as decisions about land involve changes in production along the extensive margin, while decisions about other agricultural inputs entail changes in production along the intensive margin.

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.[15] 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 turning to the impacts of agricultural insurance, there are different effects that can be measured, each of which have a specific relevance to policymakers. We begin in presenting the

[15]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).

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). Such effects estimates provide broad insight on the potential economy-wide impacts of a subsidized index insurance program such as this that is introduced at scale. We estimate the ITT effects using the analysis of covariance (ANCOVA) estimator, which has been shown to yield greater statistical power than other treatment effects estimators when the correlation in outcome measures over time is relatively low (e.g., see Frison and Pocock, 1992; McKenzie, 2012; Van Breukelen, 2006), which is typically the case with economic outcomes such as expenditures, particularly those in developing countries (McKenzie, 2012). The estimator can be operationalized using least squares by estimating the regression equation

$$Y_{i1} = \alpha + \beta Y_{i0} + \delta T_i + \sum_{j=1}^{J} \gamma_j x_{ij0} + \varepsilon_i \tag{3}$$

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; $\mathbf{x}_{i0} = \langle x_{i10}, x_{i20}, ..., x_{iJ0} \rangle$ 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.

Alternatively, policymakers might be interested in the effects of insurance on the subpopulation farmers who actually purchase insurance. The ITT effects provide a biased estimate for the average treatment effect among treated (ATT) households (i.e., those that actually purchase insurance). Assuming the correlation between purchasing insurance and the various outcomes is positive, ITT effects will be downwardly biased estimates of ATT, with the magnitude of the bias a inversely related to the proportion of those randomly assigned to be offered insurance making the decision to actually purchase coverage. Since take-up rates in the present study were so high, reliance on the ITT estimates does not result in significantly attenuated estimates of average treatment effects. However, to arrive at estimates of the average treatment effect on insured households, we next estimate local average treatment effects (LATE) by estimating the regression equation

$$Y_{i1} = \alpha + \beta Y_{i0} + \delta T_i^* + \sum_{j=1}^{J} \gamma_j x_{ij0} + \varepsilon_i \tag{4}$$

In this case, the treatment indicator of primary interest, T_i^* is a binary indicator equal to one if household i actually purchased insurance, and zero otherwise. To control for the endogeneity of insurance take-up, we instrument for this treatment indicator with an binary indicator variable capturing random assignment into the treatment group. Assuming the standard LATE conditions are satisfied (Imbens and Angrist, 1994), the LATE estimates are estimates of average treatment effects among the subpopulation of households who would always comply with their assignment.

Finally, policymakers may be interested in the effects on agricultural intensification that could be achieved by increasing the insurance coverage. From Table 5, it is clear that subsidies (whether in the form of discounts or rebates) have a positive effect on insurance coverage, so if increasing coverage leads to positive agricultural outcomes, this may be an important avenue by which agricultural policies can effect positive agricultural development. To demonstrate this potential effect, consider the following 'dose response' treatment effects regression:

$$Y_{i1} = \alpha + \beta Y_{i0} + \delta Q_{i0} + \sum_{j=1}^{J} \gamma_j x_{ij0} + \varepsilon_i \tag{5}$$

Now, the treatment indicator of interest, Q_{i0} is a (quasi-)continuous variable representing the number of insurance units (i.e., the coverage level) purchased by household i. As was the case with the binary decision to take up insurance in the LATE regression, this coverage level is also endogenous. We control for this endogeneity by instrumenting with the subsidy level (as a percentage reduction in the market price). Using this as an instrument requires that the only pathway through which the subsidy affects agricultural decisions is indirectly through its more direct effect on increasing the coverage amount (e.g., the subsidy does not act as a wealth transfer). Given both the absolute and relative magnitudes of the subsidy – no more than BDT 90 (or a little more than USD 1) and only about 10 percent of total *aman* season expenditures – this seems plausible, especially for members of the treatment group receiving rebates rather than discounts.

5.2 Results

Estimated treatment effects for the 2013 *aman* season are reported in Table 6, while estimated impacts for the 2013-14 *boro* season are reported in Table 7.[16] Focusing first on the risk mitigation effects during the *aman* season (Table 6), we find that farmers exposed to the insurance product (ITT effects) spent roughly BDT 1300 more on agricultural inputs than did farmers in the comparison group, representing a nearly 14 percent increase over comparison farmers (though this effect is only marginally significant, with a p-value on this LATE estimate of only 0.11). The increase in input expenditures is not, however, distributed evenly over all inputs. We find that, on average, purchasing insurance results in a BDT 300 increase in irrigation expenditures (a nearly 30 percent increase over comparison farmers), a roughly BDT 620 increase in fertilizer expenditures (an almost 20 percent increase over comparison farmers), and a roughly BDT 60 increase in pesticide expenditures (an almost 20 percent increase over comparison farmers), though this latter effect is not statistically significant at conventional levels, likely due to limited statistical power to detect such relatively small effects (p-value of 0.18. Given the high take-up rates, the estimated ITT effects are very similar in magnitude to the LATEs. As expected, the effect of actually purchasing insurance (LATE) among the households exposed to the insurance treatment is larger than the estimated ITT effects, though because of the efficiency loss from instrumental variables regression relative to least squares, and because the standard errors are adjusted in the LATE estimation for clustering in both the first and second stage regressions, the LATE estimates are less precise than the ITT effects estimates.

[16]In the regressions summarized in Tables 6 and 7, 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 (e.g., due to the complementary nature of many agricultural inputs), 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.

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).

Table 6 approximately here

Table 7 approximately here

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 reduce the impact of weather shock on income. On average, for farmers purchasing irrigation on a variable cost basis, having insurance incentivizes them to undertake approximately one additional irrigation operation, likely to mitigate the effects of the prolonged dry spells recorded in each of the three *upazilas*.

The effect on pesticide expenditures might be surprising at first glance, since pesticides are generally thought of as risk-reducing, and theory would predict expenditures on risk-reducing inputs would decline with insurance. However, given that this is an index insurance product, this effect is perhaps not as counterintuitive as it first appears. Although the yield risk posed by pests is covered in the average area yield index, farmers will only receive payouts if average yields are significantly impacted (whether by pests or otherwise), not just if 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 indices. 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.

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. No positive impact on cultivated area is observed, nor do we observe any increase in yields or total production, despite the increased expenditures on irrigation, pesticides, and fertilizers. Increased spending on productivity-enhancing inputs does not guarantee higher yields in every state of nature, only presumably higher yields on average. There are two likely reasons for this somewhat surprising non-result. First, we note 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 the observed increases in irrigation expenditures would likely ameliorate some of the effects of deficient rainfall during this time, there may also be 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. Second, we note that households in treatment villages had larger *aman* harvests and cultivated smaller areas at baseline, thereby resulting in higher *aman* yields at baseline. These differences were not statistically significant, so we have not controlled for these in the ANCOVA regressions reported in Table 6 (doing so merely attenuates the effect, without eliminating it), but it seems plausible that any reversion to the mean in yields could emerge as a reduction in yields that could mistakenly be attributed to a treatment effect.

In terms of the effects of an additional unit of insurance amongst the subpopulation of farmers who purchased insurance, we find positive and significant effects on fertilizer and irrigation expenditures (on the order of BDT 210 and BDT 70, respectively), as well as a marginally significant effect on overall agricultural expenditures during the *aman* season (p-value of 0.101. The effect on irrigation expenditures is perhaps a little surprising, though we are cautious as interpreting this as much more than an artifact of the data. Since irrigation plays the role of a temporary substitute for a free alternative (rainfall), there seems to be little sense in scaling investments in irrigation, especially for farmers who purchase water on a variable cost basis. The effect of an additional unit of insurance on total agricultural input expenditures (BDT 480) is of a similar magnitude to the maximum possible insurance payout (BDT 600), perhaps reflecting farmers' willingness to invest this amount in in productivity-enhancing inputs with the knowledge that they would most likely be compensated for these expenditures in adverse states of the world, and this effect is not diminished by being being increasingly susceptible to basis risk.

Table 7 reports the treatment effects estimates for the *boro* season. As with impacts during *aman* season, we find that treated farmers spend more on agricultural inputs for *boro* production than those in the comparison group. Purchasing insurance increases average *boro* expenditures by roughly BDT 1260 (10 percent) more than farmers in the comparison group. Again, as before, the increased expenditures are not spread uniformly over the different inputs. For the *boro* crop, we find that insurance led to an increase in both seed expenditures and fertilizers, on the order of roughly BDT 118 and 380, respectively, representing increases over the comparison group of 28 and 10 percent.

Importantly, 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, the payouts generate an income effect. 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 receipt of the insurance payout, 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* production in Table 6.[17]

The increased expenditures on seeds during the *boro* season is important for a couple 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., 2016). Second, saved seeds may suffer from physical and genetic deterioration over time.[18] 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 achieve comparable levels of crop emergence as they would with new seeds. Purchasing new seeds increases farmers access to the most modern and genetically pure seed material, which should have positive implications for rice production.

We find a positive (though statistically insignificant) effects of insurance on both the area cultivated under *boro* and the subsequent rice harvest, suggesting that, while the *ex ante* risk management effects during the *aman* season were exclusively tied to more intensive production, the effects observed during the *boro* season potentially engender increased agricultural production along the extensive margin. Indeed, the expansion of cultivated area may ultimately be the driving force behind the increased input expenditures. We are somewhat cautious about being too enthusiastic about these measured effects, given that they are not statistically significant at conventional levels.

[17]It is possible that risk management during the *aman* season might also produce an income effect that results in increased seed and fertilizers 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 and, consequently, no insurance payout. Because we observe higher expenditures on several 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.

[18]This is arguably less of a concern for a crop like rice, which is self-pollinating and thus more likely to retain genetic purity.

Furthermore, previous research (e.g., Abate et al., 2015) has found that farmers tend to 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. In any event, the effects on area are insignificant, so we do not place a great deal of emphasis on issues of measurement error.

As the level of insurance coverage increases, farmers invest more on agricultural inputs (by roughly BDT 410, though the only increase in expenditures on a specific input is that for fertilizers (roughly BDT 120). As was the case with the per unit increase in total expenditures during the *aman* season, the per unit increase in total expenditures during the *boro* season is of a similar magnitude to the per unit insurance payout that insured farmers received. This suggests that farmers didn't simply view the insurance payouts as compensation for the increased *aman* expenditures that evidently didn't yield any visible returns, but rather decided to funnel those payouts right back into modern agricultural inputs during the subsequent *boro* season. The fact that the increase in fertilizer expenditures is the only effect that ist statistically significant, and furthermore that the increase in fertilizer expenditures is less than half of the increase in total input expenditures, suggests that farmers took a wide variety of approaches in spending the additional income arising from the insurance payout, and this variation led to noisy treatment effects. Furthermore, it is encouraging that the total increase input expenditures across the two seasons exceeds the per unit insurance payout received, and this analyses only focuses on agricultural outcomes, abstracting from other livelihood outcomes that might also emerge from these ex post income effects. While we lack the data to properly trace farmers' mental accounting of these risk management effects, income effects, and increased expenditures, these results provide promising evidence for the role of insurance in facilitating the modernization of agriculture.

6 Concluding remarks

In this paper we present results from a novel 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, 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 very 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 actuarially-favorable prices. 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 NaN units of insurance, while those offered a rebate purchase only NaN units of insurance.

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 modern agricultural inputs during the *aman* rice growing season. Specifically, we find that insurance leads to significantly higher expenditures on irrigation and fertilizer, with a marginal impact on pesticide expenditures. The results highlight that appropriately designed insurance contracts can encourage beneficial risk-mitigation behavior, reducing moral hazard, while also increasing investments in risker – though more productive – inputs as well.

During the subsequent *boro* season, insurance results in increased expenditures on seeds and fertilizer, which in tandem contributed to a marginally significant increase in rice production. Since the insurance contract was designed to manage only *aman* season risks, these impacts cannot be considered as arising from a risk management effect. Rather, due to the timing of the insurance payouts (following the *aman* harvest and prior to *boro* land preparation), these *ex post* effects reflect the increased income or liquidity that insured households reaped, in this case most directly 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. 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 might be compelling largely 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 future 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.

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

	2013								2014						
Activity	**May**	**June**	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**	**July**
Baseline survey															
Insurance marketing															
Insurance coverage period															
Insurance payouts delivered															
Aman season															
Nursery preparation															
Land preparation															
Transplanting															
Flowering															
Harvest															
Boro season															
Nursery preparation															
Land preparation															
Transplanting															
Flowering															
Harvest															
Follow-up survey															

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

Table 2: 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)	(0.01)
Age of household head	42.74	42.56	42.91	0.35
	(0.26)	(0.37)	(0.38)	(0.53)
Household size (persons)	4.33	4.26	4.39	0.13**
	(0.03)	(0.04)	(0.04)	(0.06)
Education (highest class completed) of household head	3.52	3.37	3.66	0.29
	(0.09)	(0.12)	(0.13)	(0.18)
Total land owned and cultivated (decimal)	94.16	94.67	93.67	−1.00
	(1.98)	(2.93)	(2.68)	(3.97)
Number of years household has been a member of GUK	3.82	4.08	3.56	−0.53***
	(0.07)	(0.10)	(0.10)	(0.14)
Household has a savings account with a formal bank (=1)	0.29	0.30	0.28	−0.02
	(0.01)	(0.01)	(0.01)	(0.02)
Household cash savings is adequate	0.31	0.26	0.35	0.09***
	(0.01)	(0.01)	(0.02)	(0.02)
Household is a member of an informal savings group (=1)	0.19	0.21	0.17	−0.04**
	(0.01)	(0.01)	(0.01)	(0.02)
Household asset index (PCA)	0.06	0.01	0.11	0.10**
	(0.02)	(0.03)	(0.03)	(0.04)
Partial risk aversion coefficient	3.66	3.65	3.68	0.03
	(0.07)	(0.11)	(0.10)	(0.15)
Ambiguity averse (=1)	0.29	0.32	0.25	−0.07***
	(0.01)	(0.01)	(0.01)	(0.02)
Hyperbolic discount rate	2.70	2.78	2.62	−0.15
	(0.08)	(0.12)	(0.11)	(0.16)
Trust index (0 = least trusting; 7 = most trusting)	5.40	5.24	5.56	0.32***
	(0.03)	(0.05)	(0.04)	(0.06)
Sensitive to basis risk (=1)	0.46	0.45	0.46	0.01
	(0.01)	(0.02)	(0.02)	(0.02)
Distance from *upazila* extension office (km)	10.32	9.63	11.00	1.37***
	(0.14)	(0.19)	(0.19)	(0.27)
Aman season 2012				
Total land under *aman* rice (decimals)	52.18	53.77	50.64	−3.12
	(1.34)	(2.12)	(1.64)	(2.67)
Total harvest of *aman* rice (kg)	791.84	768.65	814.45	45.79
	(22.53)	(33.94)	(29.74)	(45.06)
Total expenditures on fertilizers (BDT)	2064.50	2154.01	1977.23	−176.78
	(60.07)	(91.34)	(78.34)	(120.12)
Total expenditures on pesticides (BDT)	287.59	290.17	285.07	−5.10
	(12.67)	(18.11)	(17.75)	(25.35)
Total expenditures on hired labor (BDT)	1652.33	1765.32	1542.16	−223.16*
	(61.20)	(101.45)	(69.33)	(122.33)
Total expenditures on irrigation (BDT)	731.44	674.57	786.89	112.33*
	(32.94)	(44.87)	(48.11)	(65.86)
Total expenditures on purchased seeds (BDT)	425.30	419.94	430.53	10.59
	(20.67)	(31.88)	(26.47)	(41.35)
Boro season 2012-13				
Total land under *boro* rice (decimals)	63.08	64.43	61.78	−2.65
	(1.43)	(2.28)	(1.74)	(2.86)
Total harvest of *boro* rice (kg)	1451.37	1452.57	1450.20	−2.38
	(34.31)	(54.07)	(42.60)	(68.64)
Total expenditures on fertilizers (BDT)	4286.54	4204.69	4366.36	161.68
	(107.57)	(149.65)	(154.47)	(215.19)
Total expenditures on pesticides (BDT)	556.37	533.52	578.66	45.14
	(30.95)	(27.53)	(54.93)	(61.92)
Total expenditures on hired labor (BDT)	2887.69	2961.54	2815.68	−145.86
	(99.13)	(149.92)	(130.28)	(198.30)
Total expenditures on irrigation (BDT)	3024.55	2955.10	3092.27	137.17
	(72.80)	(101.74)	(104.09)	(145.62)
Total expenditures on purchased seeds (BDT)	984.26	962.00	1005.97	43.97
	(51.58)	(88.25)	(54.57)	(103.18)
Number of observations	1983	979	1004	

Source: Authors.
Notes: Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Figures reported in the fifth column are based on coefficient estimates from linear regressions of the form $x_{ij} = \alpha + \beta T_i + \varepsilon_{ij}$, where x_{ij} is the characteristic over which balance is being tested (i.e., the variable described in the row header) and T_i is a binary indicator equal to 1 if the household was in a village assigned to the insurance treatment arm. Statistical significance of these differences was based on a t-test of the estimated coefficient β for each characteristic.

Table 3: Insurance policy strike points

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.

Table 4: 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
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.

Table 5: Estimates of insurance demand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	−0.829	−0.530	−0.606	−0.548	−0.681	−0.724	−0.088
	(0.759)	(1.257)	(1.254)	(1.279)	(1.309)	(1.336)	(1.030)
Level of incentive	0.067***	0.070***	0.072***	0.073***	0.087***	0.089***	
	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)	(0.022)	
Level of incentive × rebate	−0.038***	−0.040***	−0.043***	−0.046***	−0.073***	−0.077***	
	(0.010)	(0.010)	(0.010)	(0.011)	(0.020)	(0.020)	
Trust		0.017	0.024	0.011	0.029	0.028	0.035
		(0.090)	(0.090)	(0.091)	(0.088)	(0.088)	(0.074)
Hyperbolic discount rate		−0.003	−0.052	−0.004	−0.005	−0.031	−0.031
		(0.025)	(0.036)	(0.024)	(0.024)	(0.039)	(0.044)
Partial risk aversion		−0.037	−0.037	−0.101**	−0.035	−0.070*	−0.045
		(0.023)	(0.023)	(0.040)	(0.022)	(0.039)	(0.212)
Ambiguity averse (=1)		−0.029	−0.013	−0.006	−0.104	−0.080	−0.002
		(0.229)	(0.227)	(0.227)	(0.216)	(0.214)	(0.035)
Distance to ag. extension office		−0.125***	−0.125***	−0.125***	−0.231***	−0.228***	−0.021
		(0.046)	(0.045)	(0.046)	(0.079)	(0.079)	(0.090)
Hyperbolic discount rate × rebate			0.107**			0.054	0.040
			(0.043)			(0.040)	(0.037)
Partial risk aversion × rebate				0.129**		0.071	0.041
				(0.051)		(0.048)	(0.050)
Distance to ag. extension office × rebate					0.220***	0.212**	0.018
					(0.082)	(0.082)	(0.090)
Household/farm controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Discount/rebate level dummies	No	No	No	No	No	No	Yes
Number of observations	1004	1004	1004	1004	1004	1004	1004
R^2	0.202	0.265	0.268	0.269	0.302	0.304	0.402

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.

Table 6: Intention-to-treat effects, local average treatment effects, and dose responses 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			
(1)	Intention to treat effect (ITT)	263.198**	55.271	542.367**	153.810	79.433	1272.627	−0.492	−44.557	−1.066
		(112.156)	(40.932)	(234.275)	(388.869)	(93.058)	(795.428)	(3.690)	(73.765)	(0.725)
	Adjusted R^2	0.162	0.254	0.325	0.199	0.056	0.363	0.441	0.392	0.034
(2)	Local average treatment effect (LATE)	299.864**	62.973	617.929**	176.393	90.500	1449.895	−0.561	−50.767	−1.215
		(127.540)	(46.804)	(267.835)	(446.352)	(106.283)	(909.053)	(4.203)	(83.998)	(0.824)
	Adjusted R^2	0.161	0.252	0.322	0.199	0.055	0.361	0.441	0.392	0.034
(3)	Dose response effect	69.363*	22.778	212.997**	73.114	30.458	475.495	−0.064	−17.197	−0.303
		(42.056)	(14.566)	(88.991)	(135.882)	(33.873)	(289.957)	(1.234)	(24.367)	(0.263)
	Adjusted R^2	0.145	0.246	0.310	0.196	0.053	0.349	0.441	0.391	0.030
Observations		1819	1819	1819	1819	1819	1819	1819	1819	1819
Mean for comparison group at endline		986.598	354.247	2610.557	2802.118	440.828	8841.103	52.298	886.096	14.679

Source: Authors.

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. In LATE regression, binary variable indicating random assignment to the treatment group serves as an instrument for insurance take-up. In dose response regression, the level of the incentive serves as an instrument for the insurance coverage amount. Standard errors adjusted for clustering at the village level in parentheses. For LATE and dose response regressions, standard errors have been adjusted for clustering at the village level in both the first and second stages. Each regression controls for the baseline level of the outcome variable as well as household and agricultural characteristics for which there was an imbalance at baseline between treatment and comparison groups.

Table 7: Intention-to-treat effects, local average treatment effects, and dose responses of index insurance on agricultural intensification and rice production (*boro* season)

		Agricultural input expenditures during *boro* season (BDT)						Land cultivated with rice	Quantity rice harvested	Rice yield
		Irrigation	Pesticides	Fertilizer	Hired labor	Purchased seeds	Total	(decimals)	(kg)	(kg/decimal)
(1)	Intention to treat effect (ITT)	222.313	34.713	333.821*	248.839	103.574*	1108.938*	3.710	103.263	0.125
		(165.308)	(37.655)	(172.098)	(351.943)	(61.386)	(658.016)	(2.570)	(63.547)	(0.386)
	Adjusted R^2	0.234	0.172	0.395	0.349	0.064	0.474	0.480	0.602	0.065
(2)	Local average treatment effect (LATE)	253.370	39.550	380.311*	285.781	117.964*	1263.452*	4.225	117.610	0.142
		(187.385)	(42.902)	(194.146)	(404.162)	(70.116)	(746.196)	(2.923)	(72.319)	(0.439)
	Adjusted R^2	0.235	0.172	0.395	0.350	0.064	0.475	0.479	0.601	0.065
(3)	Dose response effect	90.005	16.684	121.526**	126.063	21.076	408.796*	1.305	37.140	0.066
		(61.250)	(12.816)	(58.472)	(123.770)	(20.623)	(236.741)	(0.867)	(24.422)	(0.133)
	Adjusted R^2	0.230	0.170	0.392	0.344	0.061	0.467	0.477	0.598	0.065
Observations		1819	1819	1819	1819	1819	1819	1819	1819	1819
Mean for comparison group at endline		3178.126	437.055	3669.675	3778.694	423.251	13204.076	68.128	1536.597	23.229

Source: Authors.

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. In LATE regression, binary variable indicating random assignment to the treatment group serves as an instrument for insurance take-up. In dose response regression, the level of the incentive serves as an instrument for the insurance coverage amount. Standard errors adjusted for clustering at the village level in parentheses. For LATE and dose response regressions, standard errors have been adjusted for clustering at the village level in both the first and second stages. Each regression controls for the baseline level of the outcome variable as well as household and agricultural characteristics for which there was an imbalance at baseline between treatment and comparison groups.

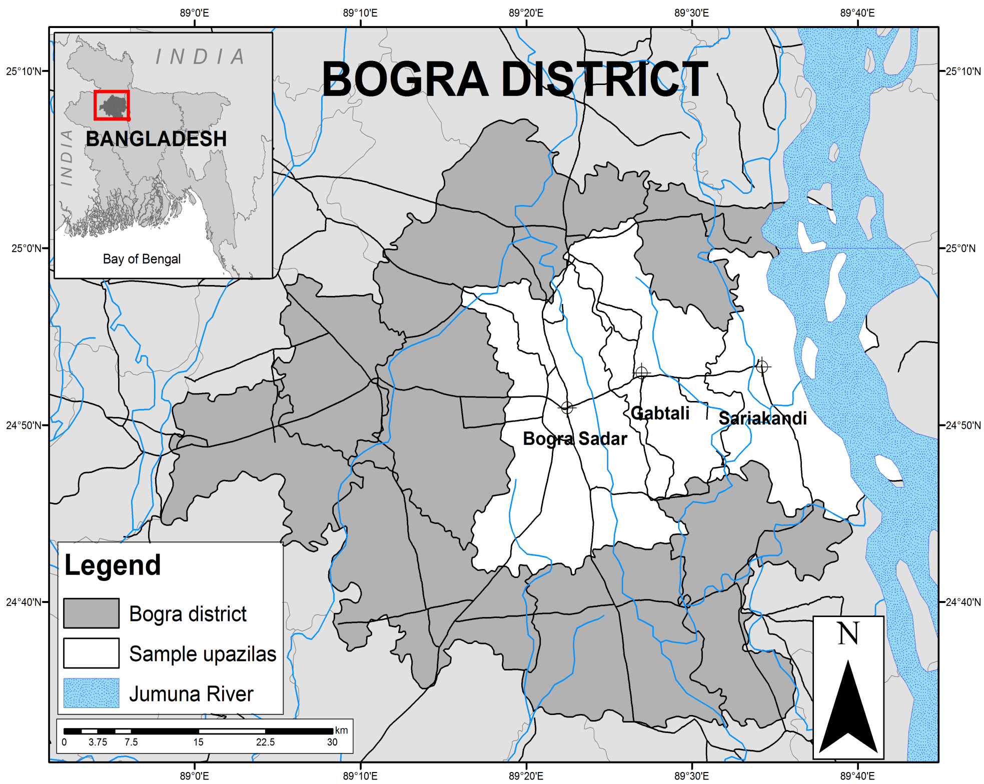

Figure 1: Location of sample *upazilas* in Bogra district, Rajshahi division, Bangladesh

Source: Authors.

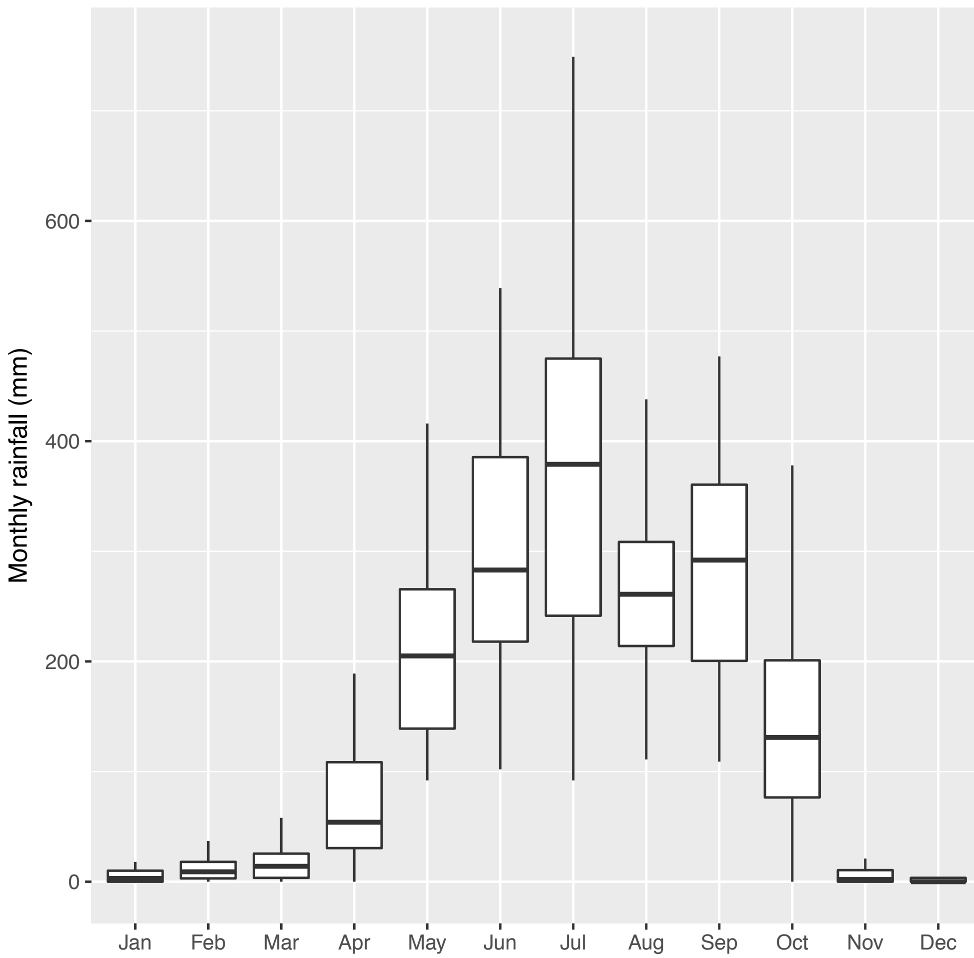

Figure 2: Historical distribution of rainfall by month, Bogra district, Bangladesh

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

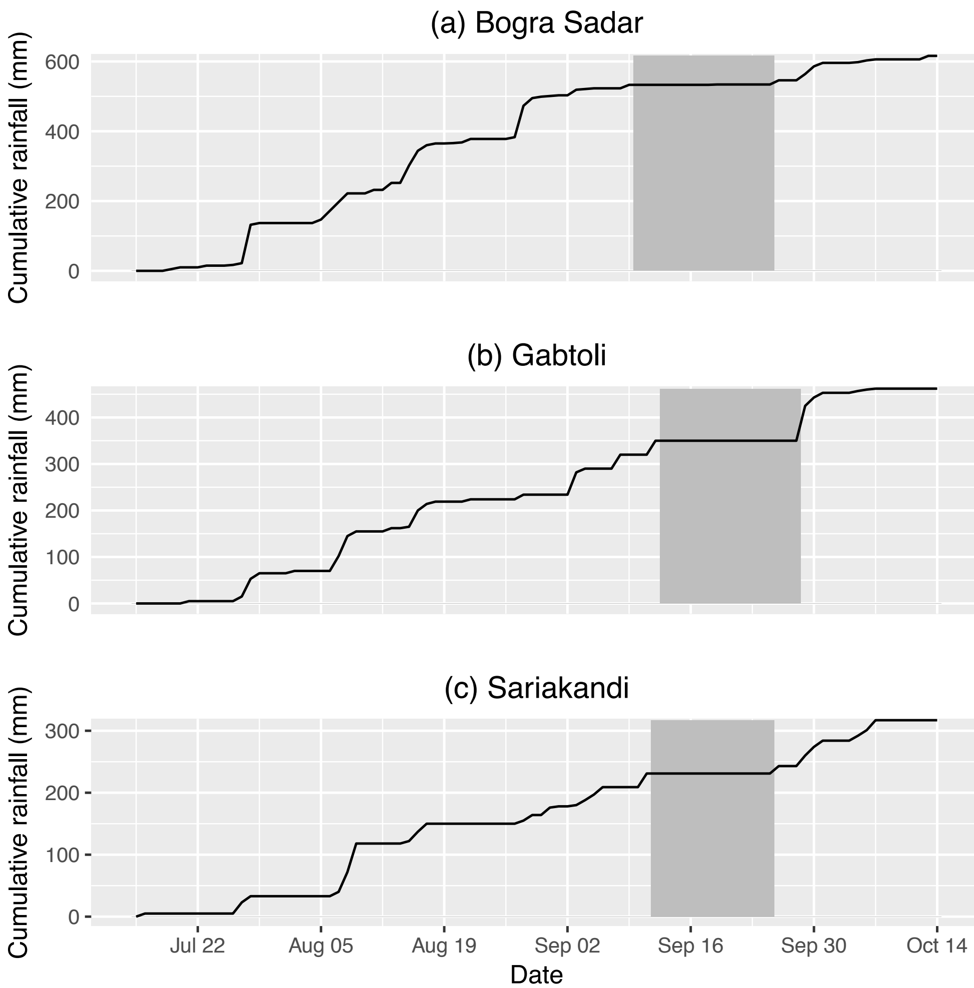

Figure 3: Cumulative rainfall during insurance coverage period (July 15 – October 14, 2013), by *upazila*

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

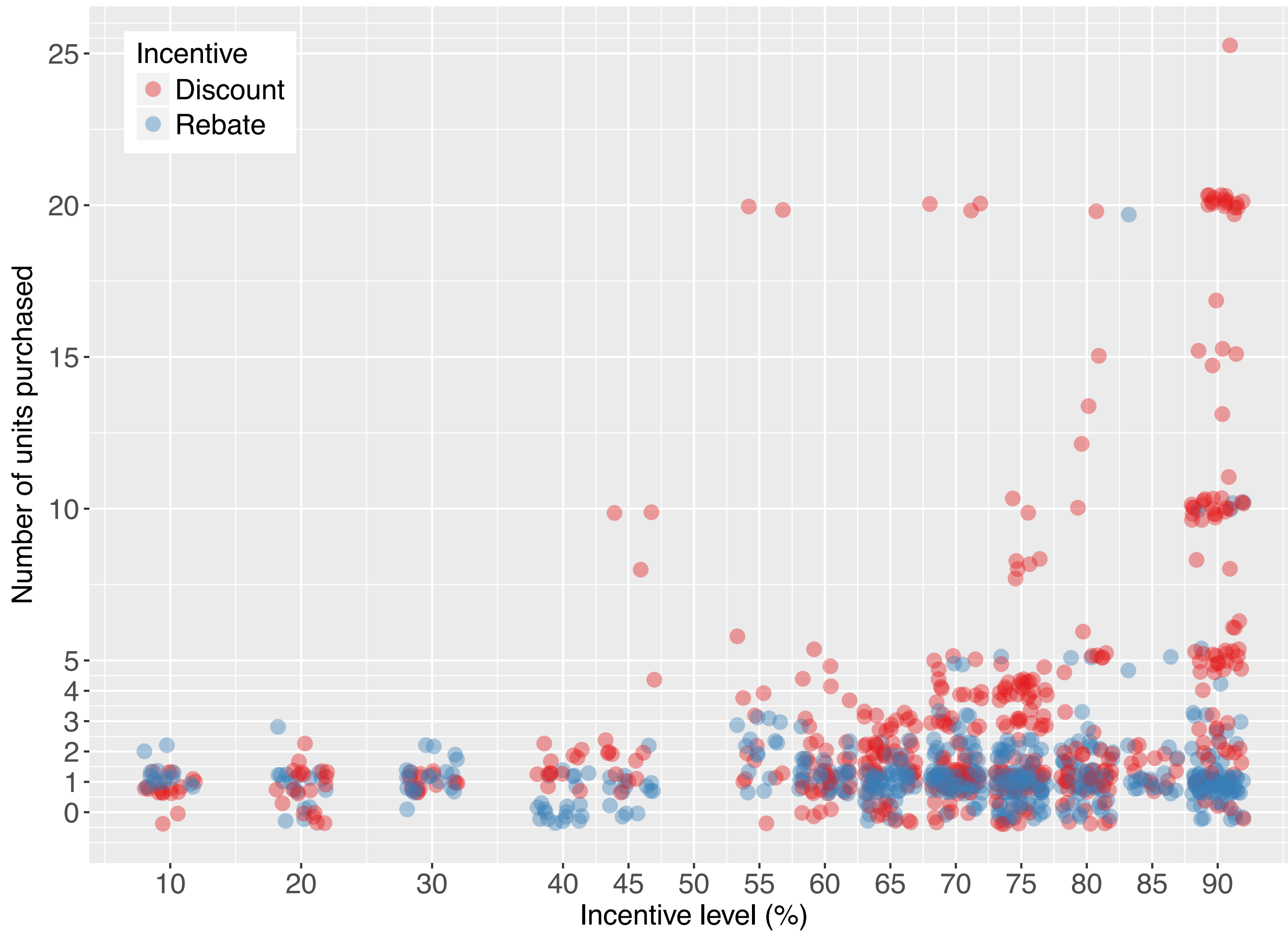

Figure 4: Scatter plot of index insurance purchases by incentive type

Note: Each dot represents a unique transaction. Transactions have been adjusted by 'jittering' to avoid overplotting.

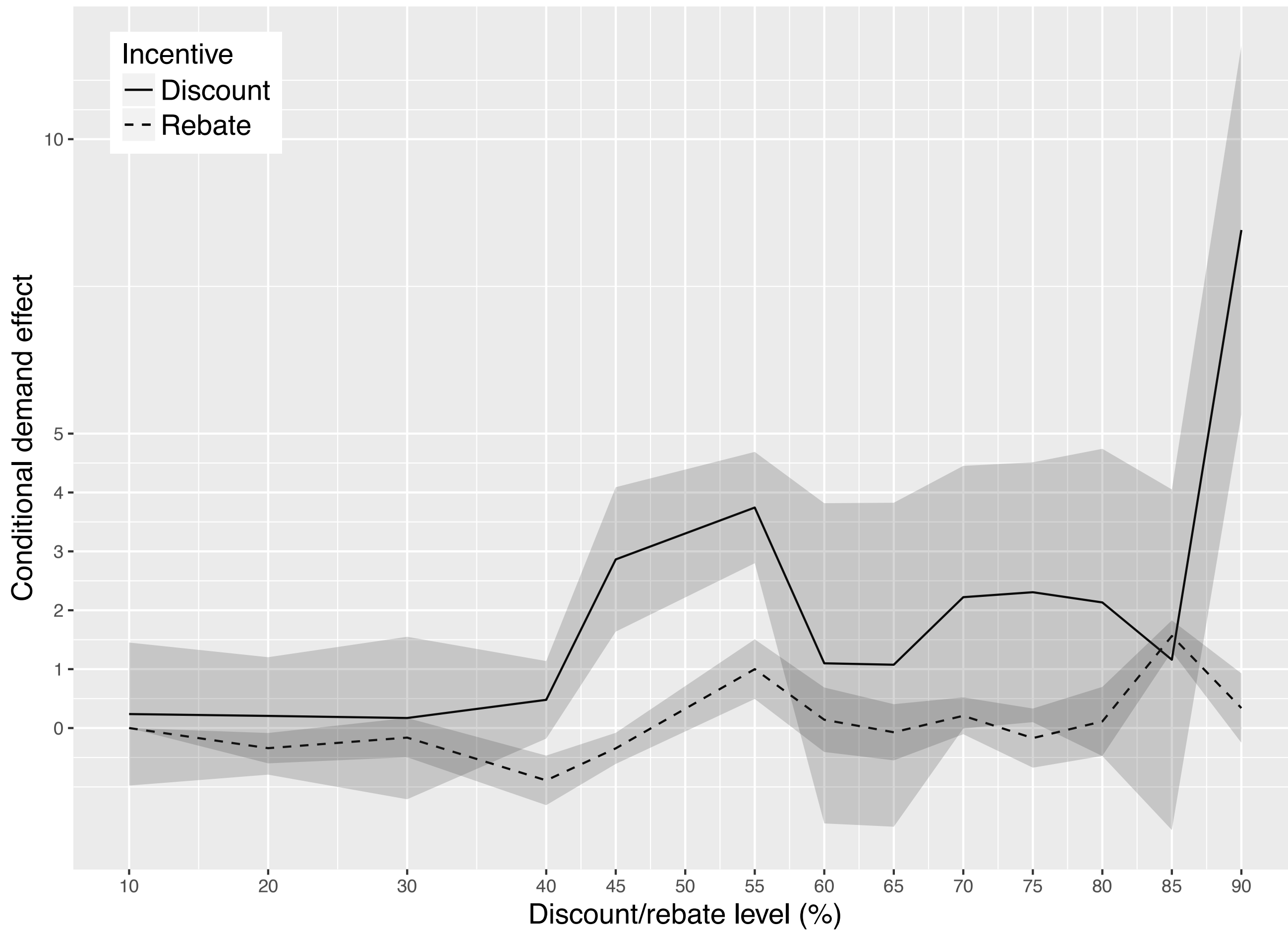

Figure 5: Demand responses to different discount and rebate levels

Note: Lines represent binary discount and rebate level coefficient estimates, with 90 percent confidence intervals depicted by shaded areas.