Demand for Weather Hedges in India: An Empirical Exploration of Theoretical Predictions

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Abstract

Income risk is substantial for farmers in developing countries. Formal insurance markets for this risk are poorly developed, and as a result there has been an increasing trend to sell weather hedges to smallholder farmers to manage their risk. This paper analyzes the demand for rainfall-based weather hedges among farmers in rural India. We explore the predictions of a standard expected utility theory framework on the nature of demand for such products, in particular testing whether demand behaves as predicted with respect to price, the basis of the hedge, and risk aversion using data from a randomized control trial in which price and basis risk was varied for a series of hedging products offered to farmers. We find that demand behaves as predicted, with demand falling with price and basis risk, and appearing hump-shaped in risk aversion. Second, we analyze understanding of and demand for hedging products over time, examining the impact of increased investments in training on hedging products as well as evidence for learning by doing among farmers. We find evidence that suggests that learning by doing is more effective at increasing both understanding and demand.

Keywords: index insurance, expected utility theory, India

JEL codes: D14, O12

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1. Introduction

Income risk is substantial for farmers in developing countries. Formal insurance markets for this risk are poorly developed, and much of this risk remains uninsured with significant consequences for investment in productive activities and the welfare of individuals. A large share of the income risk is agricultural, yet crop insurance markets are difficult in this setting (Hazell, Pomareda, and Valdes 1986) because of the small size of farms and limited formal records, and significant potential for adverse selection and moral hazard. As a result an increasing trend has been to sell weather hedges to smallholder farmers to manage their risk (Hazell et al. 2010). In India alone, more than nine million farmers purchase hedging products to insure their risk (Clarke et al. 2012).

In this paper we explore the predictions of a standard expected utility theory framework on the nature of demand for such products, in particular testing whether demand behaves as predicted with respect to price, the basis of the hedge, and risk aversion. We use the model of Clarke (2011) to develop a series of hypotheses that we test using data from a randomized control trial in which price and basis risk was varied for a series of hedging products offered to farmers in Madhya Pradesh in India. We find that demand behaves as predicted, with demand falling with price and basis risk, and appearing hump-shaped (that is, increasing and then decreasing) in risk aversion.

Typically, hedging products are not sold to individuals, given their complexity. The market for hedging products that has recently emerged for smallholder farmers in low-income countries is quite unusual in that it offers complex risk management products to individuals with limited formal education and, in most cases, no prior experience with insurance products. In this paper, we also examine how individuals learn about these products over time: We look at the impact of increased investments in training on hedging products as well as evidence for learning by doing among farmers. We find evidence that suggests that learning by doing is more effective than increasing the intensity of training.

During the past decade, index-based insurance has received considerable attention as a promising solution to the problem of imperfect insurance markets for rural households in developing countries. As a result, a number of pilot programs—generally coupled with evaluations—have been conducted throughout the world. Cole et al. (2013) report results on the determinants of demand in a number of randomized control trials conducted in India. They find that demand falls with as price increases (with a price elasticity of –0.66 to –0.88), credit constraints, and distrust of the insurance provider. Mobarak and Rosenzweig (2012) also find that demand for a weather index insurance product decreases with increases in price and distance to the weather station. This paper contributes to this literature. We also find that demand falls as price increases and as distance to the weather station increases. We estimate a negative price elasticity of 0.58 and find that doubling a household’s distance to a reference weather station decreases demand by 20 percent.

We place these findings in the context of a theoretical model of demand for hedging products and test two other predictions implied by this framework: that demand is more price-elastic when basis risk is lower and that demand is hump-shaped in risk aversion. We find that farmers located less than 5 kilometres (km) away from the reference weather station are four times as sensitive to the price of the product as farmers located at more than 12 km (for whom the basis is higher).

A number of empirical papers have found a puzzling negative relationship between risk aversion and demand for index insurance (Cole et al. 2013; Hill, Hoddinott, and Kumar 2013; and Clarke and Kalani 2011; among others). However, Clarke (2011) shows that in the presence of basis risk under index-based insurance, when premiums are above actuarially fair, a hump-shaped demand with respect to risk aversion is expected. Moreover, when premiums are actuarially fair or below, a downward-sloped relationship is to be expected. We explicitly test for these predictions and find results consistent with the above: for products with a multiple above 1, the demand increases at low levels of risk aversion but again falls at higher levels; for products with a multiple at or below 1, the intensity of demand is negatively related to risk aversion. Nevertheless—arguably because of limited power—the changes in demand at different levels of risk aversion are not statistically significant.

An additional contribution of our study to the existing literature on the determinants of demand for index insurance is our analysis of understanding and demand for hedging products over time. Our paper is among the very few to study the demand for index insurance over time (one exception is Cai, de Janvry, and Sadoulet 2013, which considers how social networks affect demand for a crop insurance contract in China). We find that a higher intensity of training has a weakly significant, short-run effect on demand with households that received more intense training—5 percentage points more likely to purchase the insurance in the season immediately following the training. However, we find that intensive training has no significant effect on general insurance knowledge when tested some months later, and as a result, unsurprisingly, we find it does not have an effect on insurance demand in the subsequent season. Instead we find that tests of general knowledge of insurance are consistent with learning by doing: Farmers who received higher price discounts have a greater level of understanding about the insurance product.

We also examine whether insurance purchases in 2011 help to explain insurance purchase decisions in 2012, as would be expected in a model of learning by doing. The evidence shows no stand-alone impact of previous purchases; however, receiving a payout in 2011 has an impact on demand during the following season. Purchasing insurance and receiving a payout is strongly positively correlated with the decision to purchase insurance in the subsequent season. A payout in 2011 increases the probability of purchasing in 2012 by around 7 percentage points.

Given that in reality most—if not all—index insurance schemes suffer from recurrent low demand, it is highly relevant to understand and quantify how demand responds to different factors. The overall take-up for the index insurance product that we consider was low in both seasons, at 6.8 and 4.0 percent during 2011 and 2012, respectively. This is in line with the take-up rates found in several other studies for index insurance in India (Giné, Townsend, and Vickery 2008 report lower than 5 percent take-up in Andhra Pradesh). Considerable government funds are being used to invest in index insurance markets with the hope that it better helps citizens manage uninsured risk. It is important to understand why demand is low. It could be because the price of these products is high (the multiples on these products range from 1.75 to 3.03, according to Cole et al. 2013, which is very high in comparison to a multiple of about 1.2 in more well-developed markets); or because of needed investments in weather station infrastructure or financial literacy; or because ultimately these products are likely to remain of marginal interest to farmers as they manage their risk. The results of this study suggest that the price and basis risk of these products are key drivers of demand and that weather hedges will prove to be a useful tool for farmers only if the price and basis risk associated with the products is substantially reduced.

The rest of the paper is structured as follows: The next section discusses theoretical predictions on the nature of demand for index insurance. Section 3 discusses the different components of the design in our study. Section 4 describes the data used for the subsequent analysis. Section 5 presents and discusses the results from the empirical analysis and contrasts them with the theory. The final section concludes.

2. Theoretical Framework and Predictions on the Demand for Index Insurance

In this section we present a simplified version of Clarke's (2011) index-based insurance model to provide an intuition on the characteristics of demand for insurance products with substantial basis risk, such as the weather hedges sold to farmers in India. We introduce testable theoretical predictions that motivate our empirical work.

Consider a representative farmer who faces an agricultural income stream, Y, that depends on two states of nature, $S = \{Loss = L, loss = 0\}$ such that $Y(S) = W - Loss$ where $Loss = L$ with probability p and $Loss = 0$ with probability $1 - p$**.** In the absence of any insurance opportunity, expected income is $E(Y) = W - pL$ and the variance of income is $Var\ (Y) = p(1-p)L^2$. The farmer's preferences over income are represented by the indirect utility function $V(.)$, and the farmer is a strictly risk-averse agent; thus $V'(.) > 0$ and $V''(.) < 0$.

Now consider an index insurance product such as a weather hedge ($Index$) that pays L with probability p and 0 with probability $1 - p$**.** The random loss ($Loss$) and the random index payout ($Index$) have identical marginal distributions[2] but are not independent. The index product is considered a good insurance instrument if it provides a payout when there is a loss and does not provide one when there is no loss. However, there is a joint probability r that there is a loss L ($Loss = L$) and the index payout is 0 ($Index = 0$) and, symmetrically, a joint probability r that there is no loss ($Loss = 0$) together with a positive index payout ($Index = L$). This joint probability, r, is the basis risk associated with the product. As a result, there are four states of nature $S = \{(Loss = L, Index = 0), (Loss = L, Index = L), (Loss = 0, Index = 0), (Loss = 0, Index = L)\}$ with probabilities $P(S)$ where $P(L,0) = r, P(L,L) = p - r, P(0,0) = 1 - p - r, P(0,L) = r$. We summarize this in Table 2.1. In this context, no basis risk means $r = 0$, which makes the random variables $Loss$ and $Index$ identical: $Loss = Index$.[3]

Table 2.1—Joint probability of income loss and index payout

Joint probability		*Index*	
		0	*L*
Loss	*0*	*1—p—r*	*r*
	L	*r*	*p—r*

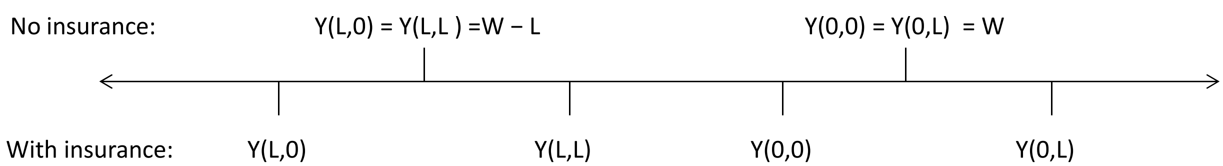
Source: authors

[2] We make the two random variables identically distributed for simplicity and to save on notation, but this condition can be easily removed.

[3] Note that if $r = p\ (1-p)$, the random variables $Loss$ and $Index$ become identically and independently distributed**.** Therefore we require $r < p\ (1-p)$ to have an index product that provides at least some insurance services.

The price of one unit of the index product is m times the actuarially fair price: pL. The farmer has the option to choose the quantity α of the index product she wishes to purchase. Her total spending is then αmpL and her net income $Y(S) = W - \alpha mpL - Loss(S) + \alpha\ Index(S)$, depending on one of the four potential states S. We summarize the income for each state with and without insurance in the real line in Figure 2.1. With insurance, the expected income is $E(Y) = W - \alpha mpL - (1-\alpha)pL$ and the variance of income is $Var(Y) = [p(1-p)(1-\alpha)^2 + 2\alpha r]L^2$. The price multiple ($m$) negatively affects the mean but not the variance. Basis risk (r) does not directly impact the expected income, but it has a positive direct impact on income variance.

Figure 2.1—Income with and without insurance



$Y(L,0) = W - \alpha\ m\ p\ L - L$
$Y(L,L) = W - \alpha\ m\ p\ L - L + \alpha\ L$
$Y(0,0) = W - \alpha\ m\ p\ L$
$Y(0,L) = W - \alpha\ m\ p\ L + \alpha\ L$

Source: authors

2.1. Maximization Problem

Given the joint probability distribution of $Loss$ and $Index$ and the price of the index product, the farmer chooses the quantity α of the insurance product that maximizes her expected indirect utility:

$$\max_{\boldsymbol{\alpha}} E\left[V\big(Y(S)\big)\right]$$

$$Y(S) = W - \alpha mpL - Loss(S) + \alpha\ Index(S).$$

The first-order condition is as follows:

$$\mathrm{E}\left[\mathrm{V'(Y(S))}\ \frac{\partial \mathrm{Y(S)}}{\partial\alpha}\right] = 0.$$

In the absence of basis risk ($r = 0$) and actuarially fair price ($m = 1$), full insurance ($\alpha^* = 1$) is the optimal solution:

$$\mathrm{p\ V'(W - \alpha pL - L + \alpha L)\ (1-p)L\ -\ (1-p)\ V'(W - \alpha pL)\ pL\ =\ 0.}$$

Under this scenario, income becomes $Y(S) = W - pL$ for all states with positive probability, and income variance is equal to zero.

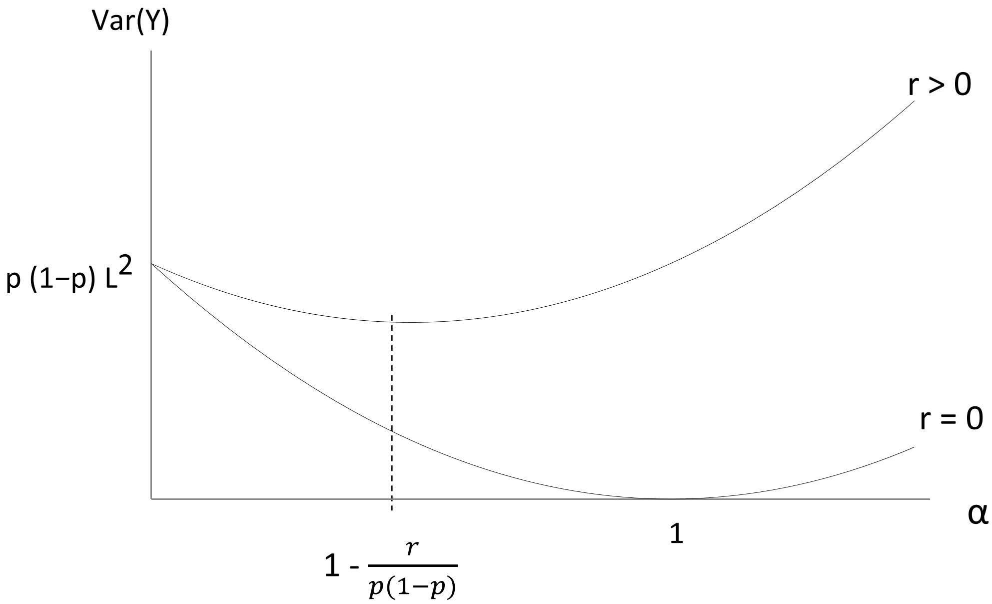
2.2. Basis Risk

Clarke (2011) shows that in the presence of basis risk ($0 < r < p(1-p)$) optimal insurance demand α^* is decreasing in basis risk r. Here, we discuss the economic intuition of that result.

After we introduce basis risk in the model, full insurance is no longer optimal. With basis risk is a positive probability of getting into a very adverse situation in which income is subject to a loss L and there is no index payout despite having spent αmpL on the insurance product; under our notation this state would be $Y(L,0)$. This is even worse than experiencing a loss without any insurance. On the flip side, there is the very lucky situation in which, despite not having a loss, the index pays out; this state would be $Y(0,L)$.

As the farmer purchases more insurance (higher α), two effects appear on the dispersion of income: Income at *middle* states in Figure 2.1, $Y(L,L)$ and $Y(0,0)$, becomes less disperse; and income at *extreme* states in Figure 2.1, $Y(L,0)$ and $Y(0,L)$, becomes more disperse. When basis risk is low, the first effect tends to dominate, and for many values of $V''(.)$ it is optimal to purchase some insurance to decrease overall net income dispersion. When basis risk is high (high r), the second effect becomes relatively more important, as extreme incomes are more likely to occur.

While the proper notion of income dispersion is not entirely reflected by income variance (as third moment is also relevant—especially in the case of highly risk-averse agents), how the variance is affected by basis risk is still informative. In the absence of basis risk, more insurance helps decrease income variance until $\alpha^* = 1$, but in the presence of basis risk, variance is higher and more insurance helps decrease the variance only until $\alpha^* = 1 - [r/p(1-p)]$, which is less than 1. When basis risk is too high ($r = p(1-p)$), a positive amount of insurance ($\alpha > 0$) only increases the variance and the optimal choice becomes not to purchase insurance at all.



An alternative path to Clarke's (2011) formal proof is to use standard comparative static analysis. We differentiate the first-order condition with respect to α and r:

$$E\left[\mathrm{V''}\big(\mathrm{Y(S)}\big)\left[\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right]^2\right]\mathrm{d}\alpha+\left[\sum_S\left(\frac{\partial\mathrm{P(S)}}{\partial\mathrm{r}}\mathrm{V'}\big(\mathrm{Y(S)}\big)\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right)\right]\mathrm{dr}=0. \tag{1}$$

The second term is equal to $\big(1-\mathrm{mp}\big)\mathrm{L}\left[\mathrm{V'}\big(\mathrm{Y(0,L)}\big)-\mathrm{V'}\big(\mathrm{Y(L,L)}\big)\right]+\mathrm{mpL}\left[\mathrm{V'}\big(\mathrm{Y(0,0)}\big)-\mathrm{V'}\big(\mathrm{Y(L,0)}\big)\right]$. By concavity of the utility function, both terms in brackets are negative and therefore the whole term is negative.[4] Hence, in Equation (1) the first and second terms are both negative, and then $\frac{\mathrm{d}\alpha^*}{\mathrm{dr}}<0$.[5]

2.3. Price

We now turn to looking at the relationship between price and demand. We show through standard comparative static analysis Clarke's (2011) result that, in the case of a constant absolute risk aversion (CARA) utility function, the optimal demand α^* is monotonically not increasing in price mpL. Since we want to keep the probability *p* and the loss *L* constant, we consider variations in prices that come through variations in the multiple m. First, note that for a given insurance coverage α, a higher multiple m reduces income in all states S by the same magnitude. In this case, the reduction in the lowest income $Y(L,0)$ is the most hurtful to the farmer's welfare and therefore induces a decrease in α^* to limit that particular welfare loss (by reducing total spending in insurance αmpL). However, a lower α has a negative impact on income of states (L,L) and $(0,L)$, and this might induce the farmer to increase α under certain conditions. Here, we show that this is not the case under a CARA utility function.

We first differentiate the first-order condition with respect to α and m:

$$E\left[\mathrm{V''}\big(\mathrm{Y(S)}\big)\left[\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right]^2\right]\mathrm{d}\alpha+E\left[\mathrm{V''}\big(\mathrm{Y(S)}\big)(-\alpha\mathrm{pL})\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right]\mathrm{dm}+E\left[\mathrm{V'}\big(\mathrm{Y(S)}\big)(-\mathrm{pL})\right]\mathrm{dm}=0.$$

Dividing and multiplying the second term by $\mathrm{V'}\big(\mathrm{Y(S)}\big)$ we get

$$E\left[\mathrm{V''}\big(\mathrm{Y(S)}\big)\left[\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right]^2\right]\mathrm{d}\alpha+\alpha\mathrm{pL}\,\gamma E\left[\mathrm{V'}\big(\mathrm{Y(S)}\big)\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right]\mathrm{dm}+E\left[\mathrm{V'}\big(\mathrm{Y(S)}\big)(-\mathrm{pL})\right]\mathrm{dm}=0,$$

where γ is the coefficient of risk aversion. The first term is negative; the second term is equal to the first-order condition, multiplied by a constant, and is thus equal to zero; and the third term is negative. Therefore $\frac{\mathrm{d}\alpha}{\mathrm{dm}}<0$.

2.4. Demand Price Elasticity and Basis Risk

We claim that the responsiveness of the demand to variations in price is a function of the degree of basis risk r. Our conjecture is that when basis risk is low, the elasticity of demand is higher than when

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[4] As shown below, $1-\mathrm{mp}>0$; otherwise, the demand for insurance is zero.

[5] Note that by the first order conditions, $E\left(\mathrm{V'}\big(\mathrm{Y(S)}\big)\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right)=\sum_S\left(\mathrm{P(S)V'}\big(\mathrm{Y(S)}\big)\frac{\partial\mathrm{Y(S)}}{\partial\alpha}\right)=0$. Multiply and divide the second term by P(S) to show that this is a negative term.

basis risk is high. Although we don't provide a formal proof of such relationship, our intuition is based on the fact that when there is no basis risk, the elasticity of demand is high; and when basis risk is extremely high, the demand for insurance is zero and unresponsive for any price above the actuarially fair price or $\mathrm{m} \geq 1$.

We have already established that in the absence of basis risk ($\mathrm{r}=0$) and actuarially fair price ($\mathrm{m}=1$), full insurance ($\alpha^{*}=1$) is the optimal solution and therefore income is constant across states such that $\mathrm{Y(S)}=\mathrm{Y}$ for any relevant state S. In this particular case we can estimate the responsiveness of the demand to a change in the multiple m (and therefore to a change in price while keeping constant p and L):

$$\left.\frac{d\alpha}{dm}\right|_{m=1,r=0}=-\frac{E\left[V'(Y(S))(-pL)\right]}{E\left[V''(Y(S))\left[\frac{\partial Y(S)}{\partial \alpha}\right]^{2}\right]}=\frac{V'(Y)}{L(1-p)V''(Y)}<0,$$

which in the case of a CARA utility function becomes $-\frac{1}{L(1-p)\gamma}<0$. And more generally from the previous section we know that $\left.\frac{d\alpha}{dm}\right|_{r=0}<0$. Now we look at the responsiveness of the demand when basis risk is extremely high: $\mathrm{r} \geq \mathrm{p}\,(1-\mathrm{p})$. We show that for any price above the actuarially fair price ($\mathrm{m} \geq 1$), the demand is unresponsive and equal to zero (see Appendix B).

2.5. Risk Aversion

Clarke (2011) shows that in the presence of basis risk and when premiums are above actuarially fair, a hump-shaped demand with respect to risk aversion is expected. Since the model presented here is a particular case of Clarke's model, the same conclusion applies here. The intuition is as follows: A risk-neutral agent won't buy an actuarially unfair product ($\mathrm{m}>1$), because the expected income is all that she cares about and expected income is decreasing in insurance coverage (α) when $\mathrm{m}>1$. As income in the worst-case scenario is decreasing in insurance coverage (α), Extremely risk-averse agents would also be unwilling to buy as they would not be willing to sacrifice an income reduction in the worst-case scenario $\mathrm{Y(L,0)}$ (income in this state is decreasing in insurance coverage, α) despite the reduction of income dispersion in middle states that insurance coverage affords. Moderately risk-averse agents would choose to have some insurance coverage ($\alpha>0$) as they would be willing to trade some income loss in the worst-case scenario against less income dispersion in middle states (L,L) and $(0{,}0)$ and income gain in state $(0,\mathrm{L})$.

3. Empirical Design

We worked with the insurance company HDFC ERGO to identify suitable villages to be included in our study. Suitable villages were defined as those that were 15 km or less from the weather station, in districts that were not notified for provision of subsidized insurance, and in villages in which HDFC had a marketing presence. Additionally, it was important to select villages that were neither too small nor too large for surveying and marketing activities. First, administrative data on the number of households within a village was used to exclude villages of fewer than 100 households and more than 500 households. This resulted in a list of about 120 villages in three districts. Second, 45 villages each in Dewas and Bhopal and 20 villages in Ujjain, 110 villages in total, were randomly selected for inclusion in this study.

The 110 sampled villages were randomly allocated into treatment and control villages: 72 treatment villages were selected for insurance to be offered in these villages. HDFC agreed that no insurance would be offered in the remaining control villages. More treatment villages than control villages were selected given the multiple treatment arms in this study. Villages in Bhopal and Dewas were allocated to treatment and control categories using a random draw with no stratification or blocking. Ujjain villages were allocated to treatment and control categories separately, on account of the later inclusion of this district. As such, stratification of the villages was along district lines. For this reason we include district dummies in our regression analyses.

Six index insurance products, simple weather hedges, were sold in each district covering deficit and excess rain at the beginning, middle, and end of the season. For every peril identified in each of the covered periods, two types of coverage were available: one for a payout in case of a lower probability event and the other in case of a higher probability event. The product was designed in such a way that the period and perils covered were the same in all the districts but each district had a different index level corresponding to a payout. Details of the products offered are provided in the Appendix. Farmers were free to choose the number and combination of policies that they wished to purchase. The policies were priced at actuarially fair prices plus administration costs. There were only minor differences in pricing between the policies offered in 2011 and 2012.

The marketing of these weather hedges was carried out by HDFC ERGO General Insurance Company in three different phases, prior to the start of each period. In 2011, sales began partway through the season, with farmers in two districts (Dewas and Bhopal) being offered policies for the middle and end of the season, and farmers in one district (Ujjain) being offered policies for only the end of the season. Given that randomization was stratified by district, this does not affect the estimation of treatment effects for 2011. In 2012, all farmers were offered all policies for the three coverage periods of the season. Moreover in 2012, a door-to-door marketing exercise was again conducted by sales agents to ensure that all households in the sample were again offered insurance.

3.1. Basis Risk

Some exogenous variation in the degree of basis risk associated with the weather hedges was introduced by installing three new randomly located weather stations that would trigger payouts. Only villages in Dewas and Bhopal were eligible for this treatment, meaning that the 12 Ujjain villages that received insurance used preexisting reference stations. The new weather stations were installed in locations selected according to the following process:

1. We randomly selected one village in which to place a new weather station. All villages very close (5 km or less) to this one were then excluded from further selection.

2. Out of the remaining villages, we randomly selected a second location. All villages very close (5 km or less) to this one were then excluded from further selection.

3. Out of the remaining villages, we randomly selected a third location.

The three villages selected using this process were Polayjagir and Talod in Dewas, and Intkhedi Sadak in Bhopal. Villages within 10 km of these sites were eligible to be serviced by these new stations. Preexisting weather stations in each of the three districts were used as a reference station for those not selected to be serviced by the new station. The full list of weather stations used in this study is listed in Table 3.1.

Table 3.1—Weather station assignment

Trigger weather station	Weather station with historical data used for product design	Number of villages covered
Dewas—Sonkatch (NCSML)	Indore (IMD)	9
Dewas—Polayjagir—New	Indore (IMD)	10
Dewas—Talod—New	Indore (IMD)	10
Bhopal (IMD)	Bhopal (IMD)	18
Bhopal—Intkhedi Sadak—New	Bhopal (IMD)	12
Ujjain-Khachrod (IMD)	Ujjain(IMD)	13

Note: NCSML refers to weather stations installed and operated by National Collateral Management Services Limited. IMD refers to weather stations run by the Indian Meteorological Department.
Source: authors using project information

Table 3.2 presents comparisons of key village characteristics between treatment villages served by a new weather station and those served by pre-existing weather stations. The results from these tests of balance indicate that villages in these two treatment groups do not differ systematically on observable characteristics.

Table 3.2—Tests of balance between villages assigned to new and old weather stations

	Mean across new weather station villages	Mean across old weather station villages	T-test of difference
Number of households	218.93	209.35	0.34
Proportion of type 0 households	0.39	0.42	–0.68
Proportion of type 1 households	0.21	0.2	0.53
Proportion of type 2 households	0.24	0.22	0.84
Proportion of type 3 households	0.05	0.05	–0.14
Proportion of type 4 households	0.11	0.11	–0.02
Proportion of female-headed households	0.04	0.04	1.12
Average education	4.43	4.38	0.16
Proportion of SC/ST/OBC	0.83	0.82	0.16
Average land owned	3.64	3.42	0.56
Km distance to weather station	5.02	10.1	–5.89
Distance to market	46.15	47.35	–0.24
Average cultivated acreage	6.93	6.72	0.36
Proportion of land that is irrigated	0.74	0.78	–0.88
Average cultivated acreage in the *Rabi*	5.72	5.9	–0.37
Proportion of land on which wheat is grown	0.64	0.66	–0.46
Proportion of land on which chickpeas are grown	0.25	0.26	–0.21
Average cultivated area in the *kharif*	6.33	6.26	0.14
Proportion of land on which soybeans are grown	0.88	0.92	–1.69
Proportion of households reporting drought in the last 10 years	0.11	0.14	–0.71
Proportion of households that previously had some agricultural insurance	0.38	0.29	1.52
Proportion of households that previously had some insurance	0.64	0.56	1.52
Proportion of households with access to agricultural loans	0.94	0.93	0.69

Note: SC/ST/OBC refers to scheduled caste, scheduled tribe and other backward castes.
Source: Listing and household survey.

3.2. Price

Exogenous variation in the price of the weather hedges was introduced by randomly allocating price discount vouchers among treatment households. If a household then chose to purchase the index insurance product, it could exercise the voucher at the moment of purchase. Based on group discussions and given the level of education of targeted farmers, we concluded that absolute numbers would be easier to understand by farmers than percentage discounts. Four levels of absolute discounts were selected, broadly equivalent to 15 percent, 30 percent, 45 percent, and 60 percent of the cheapest policy, in order to have enough price variation along a hypothetical demand curve. The level of discount received by a household held across all available insurance products for that season. For example, if a household received a Rs.45 discount voucher, the household was entitled to write off Rs.45 from the price of all index insurance products it chose to purchase.

There were important differences in price discounts between 2011 and 2012. In 2011, surveyed households received a discount voucher through a household-level random draw in two districts (Dewas and Bhopal) and through a village-level random draw in Ujjain. In 2012, discounts were randomized at the village level in all districts. The decision to provide the same level of price discount to all farmers in a village was made in response to the insurance company's concerns about a discouragement effect arising from not receiving a voucher, where farmers discriminated by the price-discount distribution process could develop a negative attitude toward the product. In addition, a villagewide price discount was cheaper to implement.

3.3. Understanding

Across all treated villages, decisionmakers in sampled households were invited to attend two hours of basic insurance literacy training in the first marketing season (2011). In these basic training sessions—which were also open to any other observers from the village—farmers were introduced to potential weather-related risks they might face and encouraged to discuss their current coping mechanisms. After this introduction, the majority of the remaining training focused on a general discussion of weather index insurance, the way in which it had been tailored to their circumstances, and the characteristics of the product. Interactive games were played with the farmers, with the games intending to illustrate the costs and benefits of purchasing these hedges. A final iteration of games helped farmers understand that the ability of the insurance company to pay their claims was not dependent on the weather outcome of other farmers. This was intended to build trust among the farmers toward the insurance company.

Additionally, 37 of the treated villages were randomly selected to receive an additional two-hour training. Households in our sample were again actively encouraged to attend the meeting, and all villagers were allowed to participate. In this additional training session the basic concepts were reiterated, and any questions and concerns that the farmers had were addressed.

Tests of balance between villages with basic training and villages with basic plus intensive training are presented in Table 3.3 and show that the two groups are balanced across common household characteristics. Some form of training was provided to all households in order to ensure a wide understanding of the product being offered. Because of this, we are able to analyze the impact of receiving intensive training with respect to receiving only basic training; we cannot estimate the impact of receiving some training or no training.

Table 3.3—Tests of balance between villages offered intensive and basic insurance literacy training

	Mean in intensive training villages	Mean in basic training villages	T-test of difference
Number of households	212.68	215.09	–0.1
Proportion of type 0 households	0.39	0.37	0.35
Proportion of type 1 households	0.23	0.22	0.49
Proportion of type 2 households	0.21	0.23	–0.7
Proportion of type 3 households	0.06	0.06	–0.52
Proportion of type 4 households	0.12	0.12	–0.48
Proportion of female headed households	0.04	0.04	0.43
Average education	4.17	4.29	–0.47
Proportion of SC/ST/OBC	0.81	0.82	–0.11
Average land owned	3.77	3.82	–0.13
Km distance to weather station	8.02	8.91	–0.67
Distance to market	47.34	48.03	–0.15
Average cultivated acreage	6.85	6.8	0.09
Proportion of land that is irrigated	0.71	0.74	–0.82
Average cultivated acreage in the *rabi*	5.65	5.65	0
Proportion of land on which wheat is grown	0.63	0.6	0.8
Proportion of land on which chickpeas are grown	0.28	0.29	–0.27
Average cultivated area in the *kharif*	6.4	6.22	0.38
Proportion of land on which soybean is grown	0.9	0.93	–1.13
Proportion of households reporting drought in the last 10 years	0.16	0.13	0.72
Proportion of households that previously had some agricultural insurance	0.3	0.38	–1.59
Proportion of households that previously had some insurance	0.58	0.57	0.19
Proportion of households with access to agricultural loans	0.93	0.92	0.37

Note: SC/ST/OBC refers to scheduled caste, scheduled tribe and other backward castes.

Source: Listing and household survey.

4. Data

A summary of the timeline of activities is provided in Figure 4.1. An initial listing exercise was conducted in all selected villages during January and February 2011, before survey work, training, and insurance sales began. The listing exercise collected basic information on household characteristics such as age, gender, and education of the household head; caste; housing structure; landownership; and main crop of production in the *rabi* season.

Figure 4.1—Timeline of activities

Data Collection		Insurance Activities				Coverage Period					
First Season—2011											
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Listing and baseline survey		New weather stations installed		Literacy training (Basix)	Discounts provided and insurance sales						
Second Season—2012											
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Follow-up survey					Discounts provided and insurance sales						

Source: authors using project information

The listing survey provides two important contributions to the study. Because much of the randomization in our design is conducted at the village level, aggregation of household data from the listing survey allows us to ensure balance across village-level statistics. Additionally, given that purchase rates of index insurance are generally found to be quite low in similar studies, it was important for us to focus our energies on households that would be relatively more inclined to purchase insurance. The information from the listing questionnaire allows us to identify these individuals and oversample them.

Studies of insurance demand in India suggest that those who purchase weather index insurance have larger landholdings and higher education levels than those who do not (Giné, Townsend, and Vickery 2008; Cole et al. 2013). Data on education of the household decisionmaker and landholding of the household collected in the listing survey were used to classify households into five categories. Households in the first category, type 0 households, are those that do not own any land. As these households were not allowed to purchase weather insurance, they were not included in the survey sample or in the training and marketing activities. Households that own land were further categorized into four types:

- Type 1 households own six acres or less of land and have a household decisionmaker with less than five years of schooling
- Type 2 households own six acres or less of land and have a household decisionmaker with five years or more of schooling
- Type 3 households own more than six acres of land and have a household decisionmaker with less than five years of schooling
- Type 4 households own more than six acres of land and have a household decisionmaker with five years or more of schooling.

We sampled 30 households from each village. On average, the proportion of type 4 households was found to be much lower than the proportion of type 1, 2, or 3 households. However, type 4 households are, a priori, the ones most likely to buy insurance. As a result, these were oversampled in our sampling strategy, such that half of the 30 sampled households would belong to this category. The remainder of the randomly selected sample in each village consisted of 3 type 1 households, 6 type 2 households, and 6 type 3 households.

A baseline survey was conducted among all sampled households in January–February 2011, immediately after the listing exercise had been completed in a village. Sampled household characteristics are displayed in Tables 3.2 and 3.3. A follow-up survey was conducted in January–February 2012 among the same households. Attrition in the follow-up survey was only 2.16 percent and not significantly different between treatment groups.

On one hand, we use data collected in the follow-up survey on understanding of and attitudes toward insurance to assess whether the interventions had the expected effect. On the other hand, to assess the impact of the interventions on realized demand for insurance, we use administrative data on insurance sales. The advantage is that these data are available for both 2011 and 2012 and are expected to be more accurate than self-reported survey data on purchases.

In 2011, HDFC insurance agents sold a total of 308 contracts in treatment villages. Take-up was 6.8 percent among sampled households. A majority of these sales, 263, correspond to the third insurance period. The remaining contracts covered the second period. The first period had no contracts because HDFC insurance agents did not get to market for it. In Bhopal and Dewas, the majority of transactions (more than 95 percent) were for the more comprehensive, more expensive contract; but in Ujjain, more than 90 percent of the purchased contracts were for the less comprehensive, cheaper policy. In 2012, the program was less successful overall, with only 185 contracts sold. Take-up was 4.0 percent among sampled households. Although the majority of contracts purchased were for the less comprehensive, cheaper policy (96 percent), there was heterogeneity regarding the covered crop phases between districts. In Bhopal, almost two-thirds of the contracts covered risks in the third phase (around harvest), with the rest mainly concentrated in the first phase (sowing). In Dewas, purchases were relatively stable across the three periods. In contrast, in Ujjain, 90 percent of the purchased contracts corresponded to the first phase.

Transaction data are summarized in Table 4.1. In both years, more than half (173 in 2011 and 182 in 2012) of the total contracts were purchased by households sampled in the baseline survey and thus invited to attend training sessions. A number of households bought multiple contracts, as indicated by the total number of households insured in Table 4.1. In 2011, although relatively few households purchased insurance in Dewas and Ujjain, on average they insured more land. This is also true of 2012 sales. The remaining contracts were bought by 125 households (in 2011) and 75 households (in 2012) that were not in the baseline sample and did not attend the training sessions. In our analysis, we will focus on uptake and demand aggregated across the entire season.

Table 4.1—Summaries of insurance purchases by district and sample

	Treated Villages			Household Sample		
	Number of sales	Acres insured	Acres insured per sale	Number of households insured	Acres insured	Acres insured per purchasing household
2011 sales						
Ujjain	115	59.5	0.5	10	8.5	0.9
Dewas	45	68.5	1.5	16	43	2.7
Bhopal	141	48	0.3	123	43.75	0.4
Total	**301**	**176**	**0.6**	**149**	**95.25**	**0.6**
2012 sales						
Ujjain	83	114	1.4	10	66	6.6
Dewas	75	150	2.0	44	85	1.9
Bhopal	27	60	2.2	33	31	0.9
Total	**185**	**324**	**1.75**	**87**	**182**	**2.1**

Source: authors using data on sales from HDFC-ERGO

5. Analysis

The random allocation of price discounts, placement of weather stations, and delivery of additional training allows us to estimate the intent-to-treat (ITT) effect of these interventions on demand for weather hedges through a direct comparison of purchases across different treatment arms.

For the most part, our dependent variable is a dummy variable taking the value of 1 if a household purchased insurance in a given season. To account for the dichotomous nature of our dependent variable, we estimate a logit model. For ease of interpretation, all tables report the average marginal effects across the sample. Since the distance of a farmer's plot to a preexisting weather station is potentially endogenous, when we consider the impact of investments on new weather stations on demand, we need to instrument this variable. We do so by following the approach in Smith and Blundell (1986), including the predicted residuals from the instrumenting regressions in the main regression. We use as the instrument whether the insurance policy for a given farmer was referenced to an existing or to a new weather station. We bootstrap the standard errors to account for the presence of a synthetic explanatory variable.

We also present some results for the quantity of insurance purchased, defined as the number of acres of land that the household insured, taking a value of zero if the household did not purchase any insurance. We estimate these specifications by ordinary least squares and by two-stages least squares when endogenous explanatory variables are included.

5.1. The Initial Impact of Marketing Interventions

In Tables 5.1 and 5.2 we present results on the impact of our three interventions—price discounts, investment in weather stations, and intensive training—on demand for weather hedges. Table 5.1 captures demand with the take-up dummy discussed above. Table 5.2 uses the natural logarithm of units purchased as a dependent variable. The price variable is defined as the natural logarithm of the price (after discount) of the cheapest policy. Since the ratio of the price between the policies for the low- and high-probability events is constant across all districts, the natural logarithm of the discounted price of the cheapest policy is a good measure of the discount value for all policies.

Table 5.1—Take-up among sampled households, 2011

	(1) Logit	(2) Logit	(3) IV Logit	(4) Logit	(5) IV Logit	(6) Logit
Log (price)	–0.135***	–0.207***	–0.133***	–0.193***	–0.338***	–0.039***
	(0.024)	(0.032)	(0.026)	(0.048)	(0.114)	(0.013)
Log (distance to weather station)	–0.018***	–0.010*	–0.042	–0.187**	–0.637**	
	(0.007)	(0.006)	(0.031)	(0.092)	(0.278)	
Intensive training	0.050*	0.020	0.049			
	(0.026)	(0.041)	(0.032)			
Log (distance) x log (price)				0.034*	0.121**	
				(0.018)	(0.054)	
Station is close						0.669***
						(0.256)
Station is close x log (price)						–0.120**
						(0.052)
Sample	Full	New station	Full	Full	Full	Far and close
Observations	2,183	848	2,183	2,183	2,183	932

Source: Administrative sales data.

Notes: Average marginal effects are reported. IV specifications instrument log of distance with assignment to a new weather station. Standard errors clustered by village in parentheses. Standard errors are bootstrapped in IV specifications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5.2—Log of units bought, 2011 and 2012

	(1) 2011	(2) 2011	(3) 2012	(4) 2012
Log (price)	–0.582***	–0.573***	–0.144*	–0.147*
	(0.133)	(0.134)	(0.077)	(0.076)
Log (distance)		–0.142		–0.011
		(0.113)		(0.075)
Intensive		0.177*		0.021
		(0.091)		(0.058)
Observations	2,183	2,183	2,183	2,183
R-squared	0.100	0.111	0.007	0.008

Source: Administrative sales data.

Notes: Standard errors clustered by village in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

First, we look at the impact of being offered a price discount. Table 5.1 shows that receiving a price discount has a substantial effect in terms of encouraging a household to purchase insurance. A 10 percent increase in price led to a 1.3 percentage point increase in take-up, which, given the low levels of average take-up, corresponds to a 19 percent increase in demand from the average. Similarly, we find a significant price sensitivity in Table 5.2. Here, the dependent variable is the natural logarithm of the units purchased, and as such, the coefficient on the price variable is a measure of the elasticity of demand. We find a considerable price elasticity of 0.58, not significantly different from the price elasticity of 0.66 to 0.88 estimated by Cole et al. (2013) for weather index insurance in other states in India.

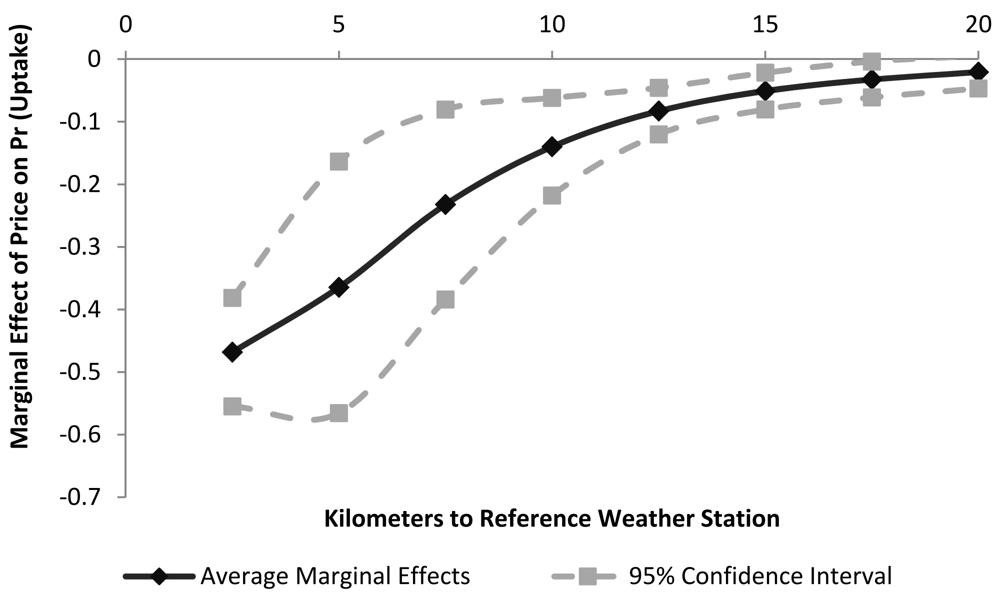
Second, we consider the impact of weather station investment. To estimate the impact of basis risk on demand, we use the distance of a household to the reference weather station in the insurance policy they were offered. Using global positioning system (GPS) coordinates of households and GPS coordinates of the weather stations (new and old), we calculate the straight-line distance between each sample household and the reference weather station. However, this distance cannot be assumed as exogenous for households that were not assigned to a new weather station. Therefore, in column 2 we present results only for those that were assigned to a new weather station, and in column 3, for all sample households but instrumenting distance with an indicator variable taking the value of 1 if the reference weather station was a new, randomly assigned station and zero otherwise. On average, households assigned to new reference weather stations were 6 km closer than those assigned to preexisting ones. Results from the first stage of this regression (Appendix Table A.2) show a significantly negative relationship between the instrument and distance. Both the reduced-sample logit and the full-sample IV estimates suggest that distance significantly reduces uptake, though using the reduced sample yields a nonsignificant estimate. Doubling the distance to the weather station from the average reduces take-up by roughly 1.25 percentage points. The relationship is no longer significant when we consider the natural logarithm of quantity purchased as the dependent variable (Table 5.2).

Third, we assess the impact on insurance demand of the intensity of training provided. Table 5.1 shows that households that were offered intensive training modules had significantly higher insurance demand. Take-up among those that were offered intensive training was about 5 percentage points higher than among those that were offered basic training only, but the effect is only weakly significant. The amount of insurance purchased (Table 5.2) was also weakly significantly higher among those that had received the intensive training.

All of the above results are robust to including household-level covariates in the estimations. This is expected, given that the tests of balance indicate no significant differences across household characteristics between treatment groups. Results are available upon request.

Thus far we have considered the impact of the treatments in isolation. However, we are likely to observe a different price elasticity for households offered a *good* insurance product, that is, with less basis risk, than for households offered a *bad* insurance product, one with high levels of basis risk. We test this assumption in columns 4 to 6 of Table 5.1 by interacting price and distance to the reference weather station. We indeed find this to be the case: The sensitivity of demand to price increases the closer a household is to the product's reference weather station. We further show this divergence in Figure 5.1, which plots the average marginal effect of the logarithm of price on the probability of take-up for households located at different distances from the reference weather station. As an alternative exercise, column 6 restricts the sample to only those households that are located less than 5 km or more than 12 km from their reference weather station. We then use an indicator variable that takes the value 1 if a household belongs to the first group. Households located less than 5 km from a weather station have a sensitivity to price three times higher (coefficient of –0.16) than that of those located more than 12 km from a weather station (coefficient of –0.04). Overall, this suggests that subsidies are more effective in encouraging demand when complementary investments are made aimed at reducing basis risk.

Figure 5.1—Price sensitivity of demand as distance to the weather station increases, 2011



Source: Administrative sales data.

5.2. Impact on Insurance Knowledge and Attitudes

Using follow-up survey data collected in January 2012, we can explore different hypotheses for the mechanisms behind the treatment effects. In particular, we examine (1) whether comprehension of the insurance product was higher for those that received the intensive training and (2) whether households with insurance linked to rainfall at a new, closer weather station believed it to better resemble the actual rainfall on their land. In Table 5.3 we assess the effect of being offered insurance on different self-reported measures of knowledge and attitudes, relative to households in villages where no insurance was offered. We see that, on average, households in villages that were offered insurance have a better understanding of insurance and trust private insurance companies more. This is the combined average effect of all activities in the villages in which insurance was offered: the general marketing insurance activities and basic training—which took place in all villages—plus the average effect of intensive training, discounts, and the placement of new weather stations in selected villages, together with the potential effects of actually having purchased insurance.

Table 5.3—Impact of offering insurance on insurance knowledge and attitudes

	(1) Knowledge about insurance product	(2) Rainfall at weather station is similar	(3) Trust government insurance to pay	(4) Trust private insurance to pay	(5) Would buy if previously good year and no payout	(6) Would buy if previously bad year and no payout
Offered insurance	0.121**	–0.003	0.011	0.063**	0.007	0.057
	(0.058)	(0.027)	(0.018)	(0.029)	(0.032)	(0.040)
Mean in control	3.02	0.14	0.93	0.19	0.76	0.27
Observations	3,237	3,209	3,234	3,231	3,235	3,232

Lagged dependent variable (from baseline survey) and district dummies included but not shown. Standard errors clustered by village in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Household survey data.

Table 5.4 disentangles some of these effects. We find that having received intensive training has no effect on comprehension of the insurance product or the other attitude-related questions that households were asked. This suggests that, to the extent that intensive training had an impact on demand, it did not come about as a result of a sustained increased in insurance literacy. It could be that households had forgotten what they learned by the time of the survey (about six months later), or it could be that the additional training served more of a marketing purpose rather than provided additional knowledge about insurance itself. We also see that households that were offered higher price discounts knew more about the insurance product being sold (perhaps due to an encouragement effect or because they were much more likely to actually buy insurance and thus to engage in learning by doing). Finally, and as expected, households that were offered insurance referenced to a new, closer weather station were more likely to believe it was a good approximation of actual rainfall on their land. Households assigned to a new weather station also knew less about the insurance product and declared themselves more likely to buy insurance in a year following no payout.

Table 5.4—Impact of training, discounts, and weather stations on insurance knowledge and attitudes

	(1)	(2)	(3)	(4)	(5)	(6)
	Knowledge about insurance product	Rainfall at weather station is similar	Trust government insurance to pay	Trust private insurance to pay	Would buy if previously good year and no payout	Would buy if previously bad year and no payout
Log (distance)	0.133*	–0.088**	–0.023	0.020	–0.089*	–0.053
	(0.076)	(0.042)	(0.023)	(0.043)	(0.047)	(0.058)
Intensive training	–0.064	–0.035	0.005	–0.021	–0.015	–0.048
	(0.063)	(0.032)	(0.019)	(0.036)	(0.038)	(0.053)
Log (price)	–0.106**	–0.008	–0.003	0.032	–0.009	0.045
	(0.043)	(0.016)	(0.011)	(0.023)	(0.021)	(0.031)
Observations	2,130	2,111	2,127	2,126	2,128	2,125

IV specifications instrument log of distance with assignment to a new weather station. Lagged dependent variable (from baseline survey) and district dummies included but not shown. Standard errors clustered by village in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Household survey data.

5.3. The Longer-Run Impact of Marketing Interventions

We now turn to the effect of the marketing interventions on take-up in 2012, the second season of sales for the index insurance product. As described in Section 3, in 2012 we again offered price discounts, randomized at the village level, but left the other treatments unchanged: No new weather stations were installed and no additional training sessions were conducted.

Table 5.5 presents specifications parallel to those in Table 5.1 but for the second season of index insurance sales. The price of the insurance policy was again strongly significant in predicting demand. The distance to the weather station was also strongly associated with purchases both in the full sample and in the subsample of villages served by the new stations, although the instrumental variables results on the full sample no longer hold. The interaction between price and basis risk also replicates the results already discussed for 2011.

Table 5.5—Take-up among sampled households, 2012

	(1) Logit	(2) Logit	(3) IV Logit	(4) Logit	(5) IV Logit	(6) Logit
Log (price)	–0.026**	–0.053***	–0.027*	–0.047***	–0.064	0.053
	(0.012)	(0.017)	(0.015)	(0.013)	(0.050)	(0.036)
Log (distance to weather station)	–0.008**	–0.013***	–0.001	–0.071**	–0.110	
	(0.004)	(0.002)	(0.015)	(0.030)	(0.146)	
Intensive training	0.005	0.022	0.005			
	(0.012)	(0.016)	(0.012)			
Log (distance) x log (price)				0.014**	0.024	
				(0.007)	(0.030)	
Station is close						0.485**
						(0.239)
Station is close x log (price)						–0.100**
						(0.050)
Sample	Full	New station	Full	Full	Full	Far and close
Observations	2,183	848	2,183	2,183	2,183	932

Source: Administrative sales data.

Notes: Average marginal effects are reported. IV specifications instrument log of distance with assignment to a new weather station. Standard errors clustered by village in parentheses. Standard errors are bootstrapped in IV specifications. *** p < 0.01, ** p < 0.05, * p < 0.1.

Interestingly, the effect of training seems to fade out over time: Although receiving intensive training considerably increased demand in the season immediately following training, it had no significant effect on demand a year later. This confirms the finding in Table 5.4 that insurance literacy training had no effect on self-reported knowledge about the insurance product during the 2012 follow-up survey. In Table 5.6 we include the discount received in 2011 as an additional control but find no effect on demand. This is quite surprising given the results in Table 5.4, which suggest that households who had received a subsidy had a much better understanding of the insurance product. Also, this result does not seem to support the existence of a discouragement (encouragement) effect of having received a higher (lower) discount in the past season.[6] In sum, the results suggest that insurance literacy training and subsidies have an immediate, but not sustained, effect on demand.

[6] This hypothesis is also rejected in alternative (not reported) specifications, such as using the difference in discount between both seasons or an indicator variable for whether the discount in 2012 was lower than in 2011.

Table 5.6—Take-up among households, 2012, including price in 2011

	(1) Logit	(2) IV Logit	(3) Logit	(4) IV Logit	(5) Logit
Log (price, 2012)	–0.026**	–0.027*	–0.047***	–0.065	0.053
	(0.012)	(0.015)	(0.013)	(0.055)	(0.036)
Log (price, 2011)	–0.002	–0.002	–0.003	–0.004	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)
Intensive	0.005	0.005			
	(0.012)	(0.013)			
Log (distance)	–0.008**	–0.001	–0.072**	–0.114	
	(0.004)	(0.015)	(0.030)	(0.155)	
Log (distance) x log (price, 2012)			0.014**	0.025	
			(0.007)	(0.032)	
Station is close					0.485**
					(0.240)
Station is close x log (price, 2012)					–0.100**
					(0.050)
Sample	Full	Full	Full	Full	Far and close
Observations	2,183	2,183	2,183	2,183	932

Source: Administrative sales data.

Notes: Average marginal effects are reported. IV specifications instrument log of distance with assignment to a new weather station. Standard errors clustered by village in parentheses. Standard errors are bootstrapped in IV specifications. *** p < 0.01, ** p < 0.05, * p < 0.1.

In Table 5.7 we test the correlation between an individual's experience with weather insurance in 2011 and demand in 2012. We find that prior experience of insurance is a strong predictor of demand. While purchasing insurance does not, on its own, have a substantial impact on demand, purchasing insurance *and* receiving a payout is strongly positively correlated with the decision to purchase insurance in the subsequent season.[7] However, observing other households in the village receiving a payout has no significant effect on demand.[8] However, we lack data on a household's social network, which would be needed to estimate this effect more precisely.

Finally, we present pooled results for the take-up in both seasons in Table 5.8. The resulting impacts simply reflect the average of the treatment effects over the first and second seasons. The interventions are, however, still significant in the pooled results.

[7] Around 10 percent (14 households) of the 2011 purchasers received a payout from the insurance product.
[8] These results are not shown but are available upon request.

Table 5.7—Take-up among sampled households, 2012, including uptake and payouts in 2011

	(1) Logit	(2) IV Logit	(3) Logit	(4) IV Logit	(5) Logit
Log (price)	–0.024**	–0.025	–0.044***	–0.046	0.055
	(0.012)	(0.016)	(0.013)	(0.058)	(0.035)
Bought insurance in 2011	0.016	0.019	0.015	0.017	0.048**
	(0.013)	(0.038)	(0.013)	(0.050)	(0.022)
Had a payout in 2011	0.073***	0.071**	0.071***	0.070	0.062*
	(0.018)	(0.036)	(0.019)	(0.046)	(0.033)
Intensive	0.005	0.005			
	(0.012)	(0.013)			
Log (distance)	–0.007**	0.000	–0.067**	–0.068	
	(0.004)	(0.016)	(0.030)	(0.164)	
Log (distance) x log (price)			0.014**	0.015	
			(0.007)	(0.034)	
Station is close					0.433*
					(0.233)
Station is close x log (price)					–0.090*
					(0.048)
Sample	Full	Full	Full	Full	Far and close
Observations	2,183	2,183	2,183	2,183	932

Source: Administrative sales data.

Notes: Average marginal effects are reported. IV specifications instrument log of distance with assignment to a new weather station. Standard errors clustered by village in parentheses. Standard errors are bootstrapped in IV specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5.8—Pooled results

	(1) Logit	(2) IV Logit
Log (price)	–0.073***	–0.073***
	(0.015)	(0.017)
Log (distance to weather station)	–0.010***	–0.020
	(0.003)	(0.017)
Intensive	0.029*	0.029*
	(0.015)	(0.016)
2012 season	–0.073***	–0.073***
	(0.015)	(0.017)
Observations	4,366	4,366

Source: Administrative sales data.

Notes: Average marginal effects are reported. IV specifications instrument log of distance with assignment to a new weather station. Standard errors clustered by village in parentheses. Standard errors are bootstrapped in IV specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4. Is Demand Hump-Shaped in Risk-Aversion?

We now turn to testing the theoretical predictions outlined in Section 2 regarding the relationship between risk aversion and insurance demand. Specifically, we examine whether a hump-shaped relationship between demand and risk aversion exists for products priced with a multiple above 1 (that is, above the actuarially fair price) and a downward-sloping relationship for products with a multiple below 1. In our experiment, insurance was in most cases priced above the actuarially fair price, and so we would expect to observe demand, on average, initially increasing with risk aversion and then falling. We show our estimates for the relationship between risk aversion (measured through a hypothetical Binswanger lottery survey question) and demand for insurance in Table 5.9. Although we do not find a significant difference in demand across different levels of risk aversion, when we graph the point estimates, we do observe the predicted hump-shaped demand for index insurance (as depicted in Figure 5.2).[9]

Table 5.9—Testing the relationship between risk aversion, price and demand

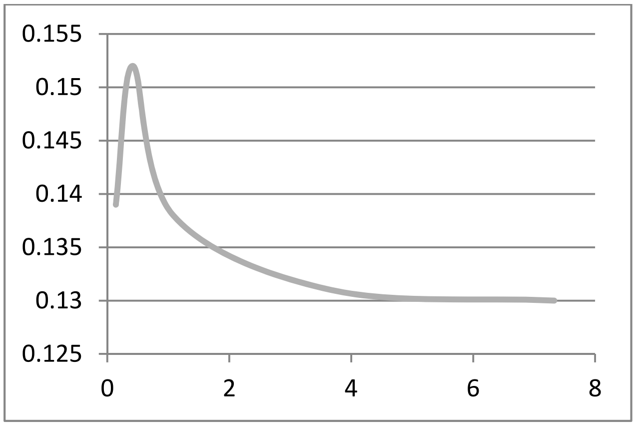
Dependent variable is 2011 uptake	(1)	(2)	(3)	(4)
Risk choice 1 (least risk averse)	0.127	–0.202	0.277	
	(0.358)	(0.518)	(0.411)	
Risk choice 2	0.340	0.382	0.278	
	(0.275)	(0.389)	(0.392)	
Risk choice 3	0.118	0.008	0.350	
	(0.290)	(0.413)	(0.348)	
Risk choice 4	–0.005	0.105	0.020	
	(0.250)	(0.328)	(0.444)	
Less risk averse				0.312
				(1.295)
log (price)				–2.586***
				(0.362)
Less risk averse x log (price)				–0.024
				(0.278)
Sample	Full	Multiple above 1	Multiple below 1	Full
Observations	2,180	1,354	551	2,183

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Administrative sales data and household survey data

[9] In all figures, we plot a spline-smoothed curve across actual coefficients of relative risk aversion, which correspond to the implicit coefficients of relative risk aversion in the answers to the Binswanger lottery.

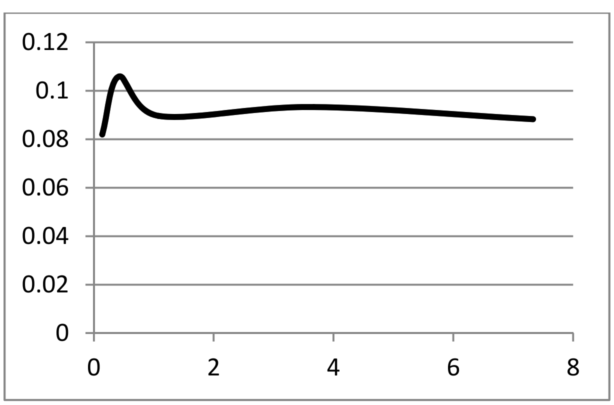
Figure 5.2—Probability of purchase against coefficients of relative risk aversion, all prices



Source: Administrative sales data and household survey data

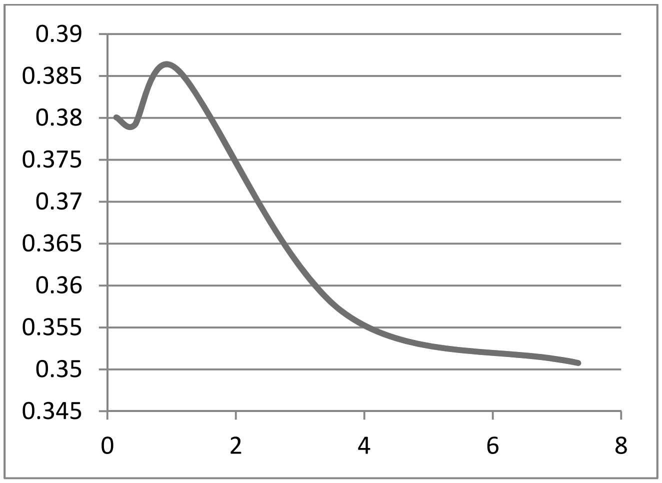
Using historical weather data, we estimate the actuarially fair price of the insurance contracts that were offered. In Ujjain and Dewas, households receiving the two highest discount values faced an insurance contract that was actuarially favorable (with a multiple less than 1). This was also the case for those households in Bhopal who received the highest discount voucher. We then separately estimate the relationship between demand and risk aversion for the subgroups of households that faced a favorable (multiple below 1) or an unfavorable (multiple above 1) insurance contract. Results are presented in columns 2 and 3 of Table 5.9. Again, we see no significant difference in demand across risk aversion, but graphing the results is still instructive (Figures 5.3 and 5.4). We observe the predicted hump-shaped demand for households facing an insurance contract priced higher than 1 (Figure 5.3) and the predicted downward-sloping demand curve for households facing a favorable insurance contract (Figure 5.4). However, there is a kink in the demand curve for households with low levels of risk aversion that is not predicted by the theory.

Figure 5.3—Probability of purchase against coefficients of relative risk aversion (when multiple is higher than 1)



Source: Administrative sales data and household survey data

Figure 5.4—Probability of purchase against coefficients of relative risk aversion (when multiple is lower than 1)



Source: Administrative sales data and household survey data

Overall, results appear consistent with theoretical predictions; although, arguably because of limited power, no significant trend across levels of risk aversion is found. If these theoretical predictions hold true, we would also expect the price elasticity of demand for insurance to be higher among those who are less risk averse than among those who are more risk averse. This is potentially a test with higher power. We show this exercise in column 4 of Table 5.9 and do not find a significant difference between the price elasticity of demand for those who are more and less risk averse.

6. Conclusions

This paper presents causal evidence on three factors that affect take-up of rainfall-based weather hedges in India: price, distance to the reference weather station (a proxy for basis risk), and insurance literacy.

We link our empirical analysis to an expected-utility theoretical framework of the demand for insurance under the presence of basis risk. In line with the predictions of the model, demand for the insurance products offered to farmers (a series of weather hedges) is decreasing in price and basis risk. These effects are robust and significant. In addition, we explicitly test a theoretical prediction from Clarke (2011) for insurance products with basis risk, where demand increases with aversion at low levels of risk aversion, while it decreases at higher levels. Empirically, we find evidence for this relationship, though the results are not strong, arguably due to a lack of power.

We also find that demand increases as product comprehension increases. This is an important finding given that these weather hedges are being offered to farmers who have limited experience with formal financial products, and certainly not with products as complex as a weather hedge. However, while both price and investment in new weather stations (as a means to reduce the extent of basis risk) are fairly effective in encouraging future demand for the product, insurance literary training seems to be of a more transient nature, with no significant impact on understanding or demand after the first year of its implementation. Price discounts had a much stronger effect on understanding, consistent with a model of learning by doing. We also find that a prior positive experience with the product—as captured by having purchased insurance *and* having received a payout during the first season—significantly encourages uptake in subsequent seasons. This could also be explained by low levels of trust in the product or the insurance company. This is an interesting avenue for future research.

The results of this study suggest that the price and basis risk of these products are key drivers of demand and that weather hedges will prove to be a useful tool for farmers only if the price and basis risk associated with the products are substantially reduced. However, it is important to consider the size of investment needed to allow well-priced, low-basis risk products to be available. Although we cannot truly compute a measure of the cost-benefit of price discounts and weather station infrastructure until we assess the (largely unknown) benefits of buying insurance and any other spillovers these interventions may bring about, we can compare the cost of each in increasing uptake by 10 percentage points.

In 2011, the cost of distributing price discounts was around US$2.97 per capita. From the estimations in Table 4.1, a discount of about Rs.135 (about $2.7) is needed to increase average take-up rates by 10 percentage points. This amounts to a total of, roughly, $5 per capita to obtain the same response in demand that can be obtained through intensive training for $20. In 2012 discounts were implemented at the village level, which basically eliminated discount distribution costs, although the price effect was weaker with a Rs.180 ($3.6) discount needed to encourage an increase in uptake of 10 percentage points. This compares favorably with the cost of insurance literacy training, which increased demand by 5 percentage points in 2011 at a per capita cost of $10.40.

In our sample, installing a new weather station increased take-up by almost 5 percentage points as a result of the increased proximity to the trigger station afforded to households in nearby villages. Installing two new stations would increase take-up rates by 10 percentage points. The cost of installing two new stations was $13.34 per household serviced, but in reality this cost can be spread across more households and across multiple years, given installing a new weather station not only encourages take-up in the year of installation but also that in subsequent years. Just spreading the installation investment of a new weather station over five years (and assuming a 20 percent interest rate) reduces the per-person annual cost to $2.23. Moreover, additional welfare benefits may stem from an insurance product with less basis risk. This is an important topic to explore in future research.

Appendix A: Supplementary Tables

Table A.1—Product design

Cover age period	Time period	Description	Index
1	Jun 25 – July 20	This period corresponds to the sowing and germination stage. Sowing usually takes place after June 15. Farmers have the option to wait until the start of the rainy season to decide when to start sowing. After sowing and during the germination phase, the major peril is excessive rain on a single day.	Maximum rainfall on any single day during coverage period
2	Jul 21 – Sep 15	This period combines the vegetative and reproductive phases. Both phases share similar perils—either excess or deficit of total rainfall during the period—although during the vegetative phase, rain deficit seems relatively more important, and during the reproductive phase, excess rain. Given that each phase by itself is relatively short, our evaluation is that it is not practical to create securities for each phase separately.	Total cumulative rainfall during coverage period
3	Sept 16 – Oct 15	This period combines the maturity phase and harvest. The major peril is excess rainfall, especially heavy rain on a single day.	Maximum rainfall on any single day during coverage period

Table A.2—First-stage results for Table 5.1

	Specification (3)	Specification (5)	
	(1)	(2)	(3)
	Log (distance)	Log (distance)	Log (distance) x Log (price)
New weather station dummy	–0.955***	–0.351	2.464
	(0.235)	(0.615)	(2.227)
New weather station dummy x price		–0.117	–1.430***
		(0.104)	(0.451)
Observations	2,183	2,183	2,183
Unrestricted R^2	0.255	0.255	0.271
Restricted R^2	0.052	0.052	0.068
Wald F-test of joint significance	16.47***	9.54***	10.00***

Standard errors clustered by village in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Administrative sales data.

Appendix B: Demand for Insurance

Demand for insurance is zero ($\alpha = 0$) when basis risk is extremely high ($r \geq p(1-p)$) for any multiple equal or higher than unity ($m \geq 1$).

We show that the expected utility with no insurance $EV(Y(S)_{\alpha=0})$ is equal or higher than the utility of having any positive insurance $EV(Y(S)_{\alpha>0})$:

$$EV(Y(S)_{\alpha=0}) \geq EV(Y(S)_{\alpha>0})$$

$$\sum_S P(S)\ \left(V(Y(S)_{\alpha=0}) - V(Y(S)_{\alpha>0})\right) \geq 0.$$

We work on the left-hand side:

$$\sum_S P(S)\ \frac{V(Y(S)_{\alpha=0}) - V(Y(S)_{\alpha>0})}{(Y(S)_{\alpha=0}) - (Y(S)_{\alpha>0})}\left((Y(S)_{\alpha=0}) - (Y(S)_{\alpha>0})\right).$$

Let's define $T(S) \equiv \frac{V(Y(S)_{\alpha=0}) - V(Y(S)_{\alpha>0})}{(Y(S)_{\alpha=0}) - (Y(S)_{\alpha>0})}$, where

$$T(L,0) \equiv \frac{V(W-L) - V(W-L-\alpha pmL)}{\alpha pmL}$$

$$T(L,L) \equiv \frac{V(W-L) - V(W-L-\alpha pmL + \alpha L)}{\alpha pmL - \alpha L}$$

$$T(0,0) \equiv \frac{V(W) - V(W-\alpha pmL)}{\alpha pmL}$$

$$T(0,L) \equiv \frac{V(W) - V(W-\alpha pmL + \alpha L)}{\alpha pmL - \alpha L}.$$

Because of the concavity of $V(.)$, $T(L,0) > T(L,L) > T(0,0) > T(0,L)$. After replacing terms we have

$$\begin{aligned} &= r\,T(L,0)\ \alpha pmL + (p-r)\,T(L,L)\ (\alpha pmL - \alpha L) + (1-p-r)\,T(0,0)\ (\alpha pmL) \\ &\quad + r\,T(0,L)\ (\alpha pmL - \alpha L)\,. \end{aligned}$$

Now we use $T(L,0) > T(L,L) > T(0,0) > T(0,L)$ and replace terms

$$\begin{aligned} &= \alpha pmL(r\,T(L,0)\ + (p-r)\,T(L,L) + (1-p-r)\,T(0,0) + r\,T(0,L)\ ) \\ &\quad - \alpha L\left((p-r)\,T(L,L) + r\,T(0,L)\ \right) \\ &\quad > \alpha pmL(r\,T(L,L)\ + (p-r)\,T(L,L) + (1-p-r)\,T(0,L) + r\,T(0,L)\ ) \\ &\quad - \alpha L\left((p-r)\,T(L,L) + r\,T(0,L)\ \right) \end{aligned}$$

$$= \alpha L\ T(L,L)\left(p^2 m - (p-r)\right) + \alpha L\ T(0,L)(pm(1-p) - r)$$

$$= \alpha L\ T(L,L)\left(r - (p - mp^2)\right) - \alpha L\ T(0,L)\left(r - m(p-p^2)\right)$$

For this expression to be non-negative, two conditions are sufficient:

$$r - (p - mp^2) \geq 0 \qquad \Rightarrow \qquad r \geq p(1 - mp)$$

$$\left(r - (p - mp^2)\right) \geq \left(r - m(p - p^2)\right) \qquad \Rightarrow \qquad m \geq 1.$$

Combining these conditions we conclude that when $r \geq p(1 - p)$ the demand for insurance is zero for any $m \geq 1$.

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