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Evidence from India

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Notices

Is there a market for multi-peril crop insurance in developing countries moving beyond subsidies? Evidence from India.

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Abstract

Researchers and policymakers have long understood the benefits of crop insurance but have been consistently disappointed by the poor performance of these programs. Rarely have programs seen sizeable take-up rates without support through large government subsidies, and in many countries, demand has been meager even at prices well below fair-market rates. Experiences from India have largely followed this trend, despite a number of large policy initiatives. Limited demand stems from low perceived value, arguably because the existing insurance products are unsuited to farmers' needs. The present study fills an important gap in rural development by improving upon existing insurance policy design by incorporating product characteristics better suited to farmers' preferences. To do so, we conducted a discrete choice experiment with agricultural households in four states in India. While farmers seem to like several of the features of policies offered under existing programs, our results suggest they would generally be willing to pay more than the highly-subsidized rate they currently pay and are also clearly dissatisfied with delayed and uncertain indemnity payments and would be willing to pay a significant premium for more assured and timely payment delivery.

JEL classification: Q10, Q11, Q18
Keywords: Crop insurance, discrete choice experiments, willingness-to-pay, India

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1. Introduction

Indian agriculture presently is marred by climate risks. Evidence seems to suggest that Indian agriculture may be in the midst of a transition to a new monsoon normal: in five of the six years between 2009-2015, monsoon rains have been weak and unevenly distributed over both time and space, and three of the seven years from 2009 through 2015 have been officially designated as all-India drought years. Total rice production has suffered as a result of these vagaries in monsoon rainfall, both as a result of decreases in harvested area as well as through reductions in rice yields. The erratic pattern of rainfall in the last few years imposes several limitations on the cultivators' decision-making behavior with regards to investments in their crops. Their perceptions of multifarious risks such as droughts, floods, market prices etc. may serve as decisive factors in their input decisions. The effects of these can be seen in their reduction of farm investments in higher-risk higher return activities, such as higher-yielding seed varieties, investing in irrigation or new machinery. It is in scenarios such as this, that crop insurance becomes relevant. By providing protection against unforeseen weather-related circumstances, insurance serves as a risk transferal mechanism, thereby encouraging farmers to undertake investments in high-value cultivation. It should therefore be expected that in setups where crop insurance is available, there is an increasing demand for the same. However, India's experience with crop insurance has not always followed an upward trend.

Agricultural insurance, specifically insurance against crop loss, has been around for many years in India. Pilot crop insurance programs implemented since 1972–73 led to the first major government crop insurance program in 1985–86, the Comprehensive Crop Insurance Scheme (CCIS) that was subsequently replaced by the improved National Agricultural Insurance Scheme (NAIS) in 1999–2000 (Nair, 2010a; Sinha, 2004). These programs used an ‘‘area approach”, whereby insurance payouts are made to all farmers in an area where average yields fall below the guaranteed yield (Nair, 2010a). Despite having several national-level programs to promote insurance, however, only about 20 percent of gross cropped area was covered under various insurance schemes as recently as 2014. The Indian Prime Minister at the time, Narendra Modi, launched a new policy in 2016 –

Pradhan Mantri Fasal Bima Yojana (PMFBY) – which replaced the NAIS.[1] The existing agricultural insurance scheme was revamped by aggregating all existing variants. Since its launch, approximately 55 million farmers have been insured, exceeding enrollment from the previous scheme by approximately 40 percent. On an average in the first two years of operation, 55 million hectares of cultivable land were insured. Opening up for participation from private insurance companies and heavily subsidizing the cost of insurance are perceived to be the key factors affecting this rise in uptake. Under this scheme, farmers pay a premium of maximum 2 percent of the sum insured during monsoon season (also known as *kharif*) sowing, 1.5 percent of the sum insured during the winter season (also known as *rabi*) sowing for food and oilseed crops, and a maximum of 5 percent of the sum insured for commercial crops, regardless of season.[2] The difference between actuarial premium rates and the farmer shares is shared equally between the union and the federal state governments. As a result, in the year 2017-18, the total premiums collected by all insurers together was INR 232 billion (USD 327 billion) of which farmers' share was INR 39 billion (USD 55 billion) and a government subsidy of INR 193 billion (USD 272 billion). By paying a premium of INR 700 (USD 10) a farmer can insure up to INR 35,000 (USD 500) of losses per hectare, assuming effective execution. Loss assessment and indemnity payments are calculated based on crop-cut experiments at the panchayat level (i.e., a collection of nearby villages). Yet only 25 percent of insured farmers purchased insurance of their own volition; the remaining 75 percent were insured as part of compulsory default coverage under the scheme where any farmer who has applied for seasonal agricultural credit is mandated to purchase insurance coverage, often without their explicit knowledge. Experiences with crop insurance thus vary widely between credit-recipients (loanees) and those not availing credit (non-loanees).

[1] 'Pradhan Mantri Fasal Bima Yojana' is translated as 'Prime Minister's Crop Insurance Scheme,' but for our purposes we will simply refer to it as India's new crop insurance program or PMFBY.

[2] According to the PMFBY Operational Guidelines, the 'sum insured' refers to the value of the threshold yield below which insured farmers are indemnified. The threshold yield is determined as the average yield from the previous seven years (excluding up to two 'calamity years') multiplied by an indemnity level (70 percent for 'high risk'; 80 percent for 'moderate risk'; and 90 percent for 'low risk'). The shortfall in yield is then the difference between the threshold yield and the actual realized yield, and claims payouts (i.e., the amount payable to farmers) is the ratio of the shortfall in yields to the threshold yield, multiplied by the sum insured.

This scenario raises a few interesting questions. Why is voluntary participation still very low when premiums for farmers are quite affordable for most? Is it the quality of insurance product and not the WTP that is a deterrent? Are certain characteristics of the insurance scheme more problematic than the others? What features should comprise an optimal agri-insurance scheme in India, and are there possibilities for trade-offs between the various components of the policy? This study attempts to answer some of these important and highly policy-relevant questions.

At present, no assessment has been done in India to determine farmers' true WTP for comprehensive multi-peril insurance policies. We try to fill this gap by conducting discrete choice experiments with farmers across four geographically variant states in India. The methodology is designed to gauge their valuation for not only the totality of a multi-peril insurance product, but also the specific characteristics, such as the coverage period, method of yield loss assessment, total sum insured, levels of actuarially fair premium rates and timing of insurance payouts. While our choice sets are agnostic to any specific insurance scheme, they include all the important attributes that are present in the current large-scale new insurance program in India. Our results, therefore, not only contribute to the broader literature on WTP for multi-peril crop insurance, but perhaps are especially valuable for actual policy makers to optimize insurance design.

2. Literature

While insurance is relevant as one of the many tools to manage and cope with all forms of agricultural risks, insurance demand behavior gets complicated by compounding of multiple factors, such as adverse selection and ambiguity aversion behavior (Elabed and Carter, 2015), thereby reducing the WTP for insurance. These traditional indemnity-based insurance programs are subject to a myriad of well-documented challenges, including information asymmetries in the form of moral hazard and adverse selection (Hazell, 1992; Morduch, 2006; Barnett et al., 2008; Miranda and Farrin, 2012). Traditional indemnity-based crop insurance programs are also prone to other challenges, including high administrative costs (in particular, the cost of assessing losses), and the covariance of insured farmers' risks that increases the insurers' risk of insolvency or, at the least, increases their costs of reinsurance. All of these challenges are perhaps most pronounced in developing countries, where information asymmetries, knowledge gaps, and other structural and operational issues are even more widespread. Moreover, despite a great deal of research, there remains relatively scant evidence to suggest that traditional crop insurance positively affects farmer welfare in either developed or developing countries (Hazell, 1992; Skees et al., 1999; Smith and Watts, 2009). Most crop insurance programs in the developed world have been propped up by large government subsidies, and many developing countries exploring such programs are following suit. Given this, and the scant empirical evidence of high WTPs for multi-peril crop insurance in developing countries, it is difficult to predict the commercial viability of such programs, particularly since even evidence from developed countries suggests that risk aversion among farmers is not high enough to pay for purely private actuarial premiums (Goodwin, 2001, Smith and Glauber, 2012).

In an assessment of Australian wheat farmers, Patrick (1988) found almost negligible willingness to pay full costs of offering insurance above the actuarially fair premium, and no buyers in the instance of loading factor exceeding 20 percent. In another assessment in Australia, farmers were not willing to pay higher than 5 percent of the actuarially fair premium (Bardsley et al., 1984). Smith and Goodwin (1996; 2010) assessed crop insurance in the US and found that farmer's willingness-to-pay (WTP) for multi-peril risk protection was not higher than the costs of bearing an insurance program. This, they argue, is not indicative of farmer's risk aversion, but instead a reflection of farmers' alternative risk management mechanisms such as diversification, off-farm employment or self-insurance. As a result, there is hardly any multi-peril crop insurance scheme that is not highly subsidized. In the US and Canada the average subsidy rates have been around 60 percent in recent times, in Spain and Portugal nearly 70 percent and in Japan roughly 50 percent (Du et al., 2016, Mahul and Stutley, 2010).

In developing countries, crop insurance is one of the many tools governments use to smooth farm incomes such as quotas, minimum price support systems, input subsidies and low interest agricultural loans, among others (Mahul and Stutley, 2010). In the presence of these, it is difficult to determine the real demand for insurance. Some options may also promote moral hazard where a combination of high input subsidy, low interest loans and insurance lead to poor management practices in a low investment - assured return setting (Hazell and Hess, 2010). In Burkina Faso, Sakurai and Reardon (1997) find that expectation of public food aid reduced the demand for drought insurance. This is known as a ‘Samaritan’s Dilemma’ (Coate, 1995). This is especially relevant where area-based approaches are prevalent for both crop insurance and disaster payments, such as loan waivers. In such a context, low risk farmers who are indemnified in an insured area may simply want to wait for a low probability disaster payment rather than investing in crop insurance. Self-insurance (grain storage, livestock sales or social networks) is another factor that conflates with demand for formal insurance in the developing countries (Kazianga and Udry, 2006, Ambrus et al., 2014). Where insurance is compulsory, that is, bundled together with crop loans, low risk farmers that have not applied for credit may not want to buy insurance knowing it cross-subsidizes high risk farmers (Report GoB, 2009). In South Asia, a peculiar interaction further complicates the understanding of insurance demand: forgiveness of agricultural credit. This hampers repayment culture and solvency of banks (Report GoB, 2009) while at the same time not translating into higher agricultural investments or productivity (Kanz, 2016). In some recent interactions with farmers in the Indian state of Karnataka, the authors discovered that indebted farmers do not visit rural banks (that are in-charge of dishing out insurance). This is out of, both, fear of having to repay and hope that there will be a political intervention near to an electoral event when outstanding loans would be forgiven (IIMA, 2018).

This implies that estimating insurance demand through observed prices (in this case, premium rates) may not yield reliable results. Therefore, in recent times, there have been some, though very limited, efforts to estimate demand or the WTP for insurance using direct valuation methods, such as contingent valuation (CVM) or discrete choice experiments (DCE). Liesivaara and Myyrä (2017) conducted a split sample DCE to include disaster aid as a constant variable in estimating WTP for different attributes of a crop insurance product in Finland. They found that expectations of disaster relief meant farmers would be less worried about crop losses. In such a situation, premiums would have to be highly subsidized for insurance take-up implying expansive use of taxpayers’ money for very low marginal benefits, which has implications for policy. Fahad and Jing (2018) use a CVM to estimate the possible premium range that farmers would be willing to pay to insure themselves from risks of flooding in a high flood prone region of Pakistan. Those who said ‘yes’ to participation in an insurance product, were given six starting bid levels in the range of 0.07 to 0.71 USD as options for the monthly premiums. There were lower and upper bounds to the dichotomous choice bids and for each choice of premium, the reasons for rejecting a higher bid were asked. This helped reveal that access to credit, irrigation, exposure to path adverse weather events and other socio-economic constraints affected insurance demand of a farmer. Arshad et al. (2016) performed a double-bound dichotomous choice (DBDC) based CVM to elicit WTP for premiums in a hypothetical insurance market for two extreme weather events, floods and droughts. The experimental sample consisted of 240 farmers from across 12 agro-climatic zones of Pakistan. Only 28 percent of respondents were willing to opt for insurance which meant a very low WTP of PKR 627 (USD 4.49) per year per acre of land for drought and PKR 659 (USD 4.72) per year per acre for floods. The WTPs were inversely related to the bid values and access to canal irrigation, whereas were directly related to incomes. Although low in values, positive WTPs for crop insurance confirmed that there is a potential to develop agricultural insurance markets in Pakistan.

The Liesivaara and Myyrä (2017) study evaluates attributes of an insurance product, but the relevance of the insights are largely limited to the EU context. Moreover, the focus has been on interaction with co-risk mitigation options. The studies in Pakistan by Arshad et al., 2016 and Fahad and Jing, 2018, on the other hand offer meaningful insights for insurance demand in a developing country context, but have two limitations: first, the assessment is for two named perils, floods and droughts, thus limiting insights on multi-peril insurance products; second, they adopt a holistic CVM approach which can only speak generally of WTP for insurance. It gives no insights on how farmers value the various attributes (such as coverage period, timeliness of indemnity payments or yield loss assessment accuracy) within an insurance product, and thereby, does not help in optimizing insurance design. An assessment of WTP for multi-peril insurance in India, that also evaluates the preferences for attributes, is therefore, novel and helps to understand insurance demand behavior in developing countries more comprehensively. This is especially true in a context where one of the largest government subsidized multi-peril insurance programs in the world is currently operational. It provides an opportunity to validate outcomes and experiment with optimized insurance design.

3. Discrete choice experiment methodology

3.1 Random utility model

The present study uses discrete choice experiments to better understand Indian farmers' preferences for various elements of crop insurance. Discrete choice experiments allow researchers to analyze stated preferences for products or services, but beyond that they allow researchers a means for parsing out preferences for specific characteristics or attributes of a good or service. This is particularly useful if the researcher believes, as Lancaster (1966) suggested, it is not the good or service that is the object of utility, but rather it is from the underlying characteristics of the good or service from which utility is derived. In a discrete choice experiment, preferences are elicited through survey participants' responses to a series of hypothetical choice scenarios. These survey-based exercises are referred to as experiments because the researcher controls the combination of product characteristics to which the survey participant is exposed.

We assume that observed choices arise from a process of utility maximization (McFadden, 1974). Specifically, within the context of a discrete choice experiment, it is assumed that the observed (stated) choice that an individual makes within a particular choice scenario is the choice that, on average, maximizes her utility among the set of potential alternatives. Utility can be conceived of as consisting of both a systematic, deterministic component, and a stochastic component. The deterministic component reflects individual tastes and preferences that map the expression of product characteristics directly into utility, while the stochastic component reflects, among other things, random variations in tastes and preferences and errors in optimization. We can write our random utility model as:

$$u_{ijt} = \alpha_i p_{ijt} + x'_{ijt}\beta_i + \varepsilon_{ijt} \qquad (1)$$

where u_{ijt} is the observed indirect utility (i.e., the utility of the utility maximizing option j) obtained by individual i during choice scenario t; p_{ijt} is the price of option j faced by individual i during choice scenario t; x_{ijt} is a vector of (non-price) insurance policy characteristics or attributes; α_i represents individual i's preferences for policy price; β_i is a vector of preference weights for the corresponding elements of x_{ijt}; and ε_{ijt} is a Gumbel (Extreme Value Type I) distributed error term with farmer-specific variance $Var(\varepsilon_{ijt}) = \sigma_i^2(\pi^2/6)$, where σ_i is a farmer-specific scale parameter. In many applications, it is assumed that there is no heterogeneity in this scale parameter, and furthermore the scale parameter is simply normalized to 1 for ease of computation (i.e., $\sigma_i = \sigma = 1$). Taking partial derivatives of u_{ijt} with respect to the attributes provides estimates for the change in utility associated with incremental changes in the expression of the attributes; in other words, the β_i terms can be directly interpreted as marginal utilities. The ratio of two marginal utilities is directly interpretable as the marginal rate of substitution between the two attributes (i.e., the rate at which an individual would be willing to give up a unit of the attribute in the denominator to acquire an increment of the attribute in the numerator). If one of the marginal utilities is the marginal utility of income, then the marginal rate of substitution with respect to income is an estimate of WTP. We are rarely able to directly observe the marginal utility, but this can be proxied by the marginal disutility of product cost. Since cost is almost always deemed to be one of the important features driving purchase decisions, it is almost universally included as an attribute in a DCE. An estimate for the WTP for a specific attribute would therefore just be the ratio of the marginal utility of the attribute to the marginal disutility of product price.

If one assumes that, in addition to homogeneity in the scale parameter, preferences are fixed in the population, then estimating marginal utilities and arriving at estimates for WTP is relatively straightforward using conditional logit estimation. The assumption of fixed (or constant) preferences in the population is quite restrictive, however, and imposes some potentially unrealistic assumptions on, among other things, the substitution patterns that are permitted by the model. A common approach to incorporating preference heterogeneity is to estimate the choice model using a mixed logit (also known as a random parameter logit) model. Under this approach, the researcher assumes a distribution for the preference parameters, and derives an estimate for WTP as the ratio of the random parameters. This approach, however, can lead to distributions for WTP that have undefined moments (e.g., the ratio of two normally distributed random variables takes a Cauchy distribution, for which neither the mean nor the variance are defined).

3.2 Estimation in willingness-to-pay space

Even if we permit preference heterogeneity, there is still the potential violation of scale homogeneity. If we permit scale heterogeneity, then we cannot simply proceed with a conventional mixed logit estimator. Note that, since utility is ordinal, we can divide equation (1) by the scale parameter to obtain a scale-free equivalent (Scarpa et al., 2008):

$$u_{ijt} = (\alpha_i/\sigma_i)p_{ijt} + x'_{ijt}(\beta_i/\sigma_i) + \nu_{ijt} \tag{2}$$

where, now, ν_{ijt} is an i.i.d error term with constant variance $\pi^2/6$. We can re-write the re-scaled utility coefficients as

$$u_{ijt} = \lambda_i p_{ijt} + x'_{ijt}\psi_i + \nu_{ijt} \tag{3}$$

Importantly, note that if σ_i varies randomly in (2), the utility coefficients in (3) will be correlated, since σ_i enters into the denominator of each of the re-scaled utility coefficients. Even if σ_i does not vary, the utility coefficients could still be correlated simply due to correlations among tastes for various attributes (Scarpa et al, 2008). Since the WTP for a given attribute is the ratio of the marginal utility of that attribute to the marginal (dis-)utility of the policy price, we can write $\gamma_i = \psi_i/\lambda_i$, and can re-write (3) as

$$u_{ijt} = \lambda_i\left[p_{ijt} + x'_{ijt}\gamma_i\right] + \nu_{ijt} \tag{4}$$

which re-parameterizes utility in WTP space rather than preference space (Train & Weeks, 2005; Scarpa et al., 2008). Now, rather than assuming the distributions for the marginal utilities (the β_i terms), the researcher can directly specify the distribution for (individually-scaled) WTP (the γ_i terms) without having to worry about ratio distributions with undesirable properties. Consequently, researchers have much more direct control over the distributional features of marginal WTP in the underlying population under this specification than they would otherwise (Thiene & Scarpa, 2009). Furthermore, Train & Weeks (2005) and Hensher and Greene (2011) have found that this transformed model generally produces more reasonable estimates of WTP than when WTP is calculated as the ratio of utility parameters. This model can then be estimated by appealing to the generalized multinomial logit (GMNL) model developed by Fiebig et al. (2010), which Hensher and Greene (2010) have demonstrated is a generalization of choice models estimated in both preference space as well as WTP space.

To allow for even greater flexibility in estimation, we consider the possibility that the randomly distributed WTPs for the different insurance product attributes could be correlated. As was previously mentioned, if there is scale heterogeneity, then WTPs will be correlated by definition, and even if there is no scale heterogeneity, there is the possibility for correlated WTPs simply due to correlation among preferences for different attributes. Hensher, Rose, and Greene (2015) have further noted that, in virtually all data sets, there are likely unobserved effects that are correlated among alternatives in a given choice situation and allowing for WTP parameters to be correlated is one way to account for this. Failing to control for this can lead to imprecise estimates of WTP, which has obvious implications for the reliability of the policy implications that be derived from these estimates (Mariel & Meyerhoff, 2018).

3.3 Experimental design

While there are potentially innumerable different dimensions with which to characterize and differentiate insurance products, to maintain tractability we are necessarily limited in the scope of attributes over which we can attempt to elicit preferences. As such, we narrowed the field of potential attributes to those which we assumed would be particularly salient in farmers' minds when they evaluate risk management alternatives. In particular, we were interested in estimating farmers' preferences for the insurance coverage period, the method of loss assessment, the delivery of insurance payments, the coverage amount (referred to in the Indian context as the insured sum), and the cost of insurance. For the coverage period, there are several potential alternatives that insurance providers could consider. For example, under PMFBY, insurance covers the entire period from pre-sowing until after harvest. Other alternatives could include only the period from sowing until harvest, or merely pre-sowing or post-harvest.

For the method of loss assessment, we consider not only the crop-cutting experiments at the village or panchayat level that are currently being utilized under PMFBY, but also loss assessments from remote (e.g., satellite-based) sensors, as well as rainfall-based indices, in which insurance payments could be issued if rainfall at the district level falls below 75 percent of long-run historical averages. While crop-cutting experiments may provide loss assessments that are highly correlated with a particular farmer's on-field experiences, they are very costly to administer and highly susceptible to accidental and purposeful measurement errors. Other methods for assessing losses, such as using remote sensors, are generally quite inexpensive and may eliminate problems of moral hazard and adverse selection, but typically either lack a high degree of transparency (in the case of remote sensing technologies) or exhibit relatively low correlations with actual on-farm performance (in the case of rainfall-based weather indexes), especially in irrigated agricultural systems.

The timing of insurance payments – in particular the long delays that farmers endure – has been often identified as a problematic feature of crop insurance in India, including under PMFBY. We were interested in seeing whether farmers would be willing to pay a premium for an insurance policy that would provide assured, timely payments if farmers experienced a loss during the coverage period. In the discrete choice experiment, we allowed for insurance policies to provide indemnities within six weeks of losses being assessed, with 100 percent certainty, or for a 50 percent chance that payments will arrive within six weeks of losses being assessed, and a 50 percent chance that payments will be delayed for more than 6 months.

Perhaps of greatest interest to both insurance providers and their clients is the cost of insurance. Controlling for policy price is important because it allows for direct estimation of a monetary welfare metric – namely, WTP. Recall that the preference parameters β can be interpreted as marginal utilities. The ratio of any two marginal utilities can be interpreted as the marginal rates of substitution. The ratio of the marginal utility of a policy attribute with respect to the marginal utility of income (or the marginal disutility of policy cost) provides a direct estimate of the amount of money an individual would be willing to give up (or would demand) in exchange for an incremental increase in the expression of the policy attribute. While farmers are currently only asked to pay a mere 1.5-2.5 percent of the insured sum as premium under PMFBY, the very low and seemingly arbitrary figures might not truly reflect the value that farmers derive from crop insurance. In our discrete choice experiment, we allowed for the policies to have three different premium rates, including 2.5 percent, 4 percent, and 10 percent.

We also included in our experiment a variable capturing the insured sum of the hypothetical insurance policies. This is not because we were especially interested in preferences for larger policies versus smaller policies (we would assume a priori that larger payouts would be preferable to smaller payouts), but more so because we needed for there to be a baseline against which the study participants could evaluate the policy premium and the other insurance policy characteristics. In our experiment, we allowed for the insured sum to take three possible levels, specifically INR 20,000, INR 30,000, or INR 40,000 per hectare. Table 1 summarizes the various attributes of an insurance policy and their various level included in this experiment.

Expanding equation (4) based on the above discussion of product attributes, our base utility function accounting only for main effects can be written as:

$$u_{ijt} = \lambda_i \big[Premium_{ijt} + \gamma_{i1} Cov_{1,ijt} + \gamma_{i2} Cov_{2,ijt} + \gamma_{i3} Cov_{3,ijt} + \gamma_{i4} LA_{1,ijt} + \gamma_{i5} LA_{2,ijt} + \gamma_{i6} Timing_{ijt} + \gamma_{i7} Sum_{ijt} \big] + \varepsilon_{ijt} \tag{5}$$

where Cov_1, Cov_2, and Cov_3 are binary variables corresponding to insurance coverage from sowing to planting, coverage during pre-sowing, and coverage during post-harvest, respectively, with the coverage period extending from pre-sowing to post-harvest serving as the reference category. Similarly, LA_1 and LA_2 are binary variables corresponding to loss assessments from remote sensors and rainfall-based indices, respectively, with loss assessments from crop-cutting experiments at the village or panchayat level serving as the reference category. $Timing$ is a binary variable equal to one if the insurance payment is guaranteed to be delivered within six weeks of the loss assessment, and zero otherwise. The $Premium$ and Sum terms are continuous variables capturing the monetary cost farmers are required to pay insurance and the insured sum, respectively. While the premium attribute was previously discussed percentage rate of the insured sum, this rate was converted into a monetary figure when participants completed choice tasks by multiplying the premium rate by the insured sum for each choice alternative.

Because a full factorial experimental design – consisting of all possible combinations of insurance policy attributes across the competing alternatives – would be intractable in any real-world research setting, we set out to create a fractional factorial design that satisfied some well-established design criterion. In our particular case, we specified an orthogonal experimental design with three hypothetical alternatives in each choice set, and underlying utility functions consisting of all main effects and first-order interaction effects.[3] The experimental design was generated using Ngene 1.1.2, a software package specially-designed for generating discrete choice experiments (Ngene, 2014). In sum, the experimental design resulted in a total of 36 unique choice sets, each consisting of three hypothetical alternative insurance policies. The 36 choice sets were blocked into six groups of six choice sets each. Each household in the sample was then randomly allocated to one of the six groups, and then would be expected to respond to the 6 choice sets assigned to that specific choice set group.

4. Data

The data used in the present study come from a household survey conducted across four Indian states (Gujarat, Himachal Pradesh, Karnataka, and Uttar Pradesh; see Figure 1). While not intended to be nationally representative, the diversity of state coverage allows for some heterogeneity in agro-ecological and social conditions. The survey and discrete choice experiment were conducted from mid-February to mid-March 2018, with most agricultural questions targeted toward the 2017 monsoon (kharif) 2017. Data were collected with the assistance of Agricultural Economic Research Centers (AERC's) of the Ministry of Agriculture in India using computer-assisted programming. Three representatives from each of the AERC's based out of the four states and independently-recruited survey enumeration staff were trained for data collection using the SurveyCTO computer-assisted personal interviewing (CAPI) platform on Android tablets. From

[3]Orthogonal experimental designs have the properties of attribute balance and independent estimability of all parameters. In practice, this implies that each attribute column in the design matrix is uncorrelated.

each of the four states, two districts were sampled based on their share of primary crop cultivation in the state. Within each district, two blocks were randomly selected, with three villages subsequently selected at random from each block. Within each village, 12 households were randomly selected from village lists, resulting in an initial sample of 576 households. Respondents were administered a set of survey questions that sought information on their demographic characteristics, cultivation practices, household asset ownership, income sources and experience with insurance policies, translated in their local languages. The discrete choice experiments were also administered using standardized, scripted protocols. Both the survey questions and the discrete choice experiment were administered in the primary language in each state (Gujarati in Gujarat, Kannada in Karnataka, and Hindi in both Uttar Pradesh and Himachal Pradesh). Table 2 summarizes the characteristics of households in the sample on both a pooled and statewise basis.

5. Results

5.1 WTP estimation

Table 3 presents results our base estimates of WTP for insurance product features under two specifications. Column (1) reports results from a generalized mixed logit regression assuming that WTP parameters are uncorrelated, while column (2) reports results permitting free correlation of the WTP parameters. Under both specifications, we permit both preference and scale heterogeneity, with the WTPs assumed to be normally distributed. The upper panel in Table 3 reports the estimates of the mean WTP for the corresponding attributes, while the lower panel reports the corresponding distribution parameters (standard deviations).

Although there is not a sizeable difference in model fit between the two specifications, nor are there dramatic changes in the WTP coefficient estimates, the model permitting free correlation in WTP parameters is superior to the more restrictive specification assuming that the WTP parameters are uncorrelated based on a likelihood ratio test. Additionally, when we permit correlations, all of the means and standard deviations for the WTPs are statistically significant, indicating that not only are the mean WTPs significantly different from zero, but also that there is a significant amount of heterogeneity in insurance policy preferences within the population.

Indeed, when we allow for correlated WTP parameters, the standard deviations of the WTP distributions are all greater than when we preclude correlations. For the discussion that follows, we will rely upon the estimates assuming the WTP parameters are correlated. Figure 2 illustrates the empirical distributions of farmers' WTP for the various insurance policy attributes considered in the present study.

Interestingly, the estimates suggest that farmers would be willing to pay significantly higher premiums than they currently are asked to pay. The coefficient of sum insured is approximately 0.1, meaning that if the sum insured rises by one unit (here, 1 unit=INR 1,000), they would be willing to pay roughly INR 100, or about 10 percent of the sum insured. While that is close to the actuarially-fair cost of insurance (Joint Group, 2005), it is still quite low relative to what would likely be needed for insurance to be commercially viable without large government subsidies, but the premium is about 5 times higher than what farmers are required to pay for crop insurance under PMFBY. For example, for a base policy with an insured sum of INR 30,000 per hectare, these results suggest that farmers would be willing to up to INR 3,000 per hectare. Under PMFBY, where farmers are typically only asked to pay at most a premium of 2 percent of the sum insured, they cost to farmers would only be INR 600 for a comparable policy.

For insurance policy attributes that enter the utility function as binary variables (coverage level, loss assessment, and timing of indemnity payments), the omitted category is always the status quo under the existing policy regime. Consequently, many of the estimated WTPs reported in Table 3 can be interpreted either as premia that individuals would be willing to pay (in the case of guaranteed indemnity payments within 6 weeks of loss assessment) or discounts that would be demanded (in the case of coverage period or loss assessment methods) for alterations of the status quo insurance policies. For example, farmers in our sample would require discounts for policies with shorter coverage periods (i.e., anything other than pre-sowing to post-harvest). These required discounts are quite sizeable for policies that cover only the pre-sowing period (INR 5,000) or only the post-harvest period (INR 4,800). Both of these required discounts exceed the INR 3,000 that we might expect farmers to be willing to pay for a hypothetical base policy with an INR 30,000 insured sum. Even in the choice experiment itself, the highest possible cost that farmers faced was INR 4,000 (a maximum 10 percent premium on a maximum insured sum of INR 40,000 per hectare). The fact that these implicit discount requirements are so large speaks volumes about farmers' preferences and clear dissatisfaction with the limited coverage offered by these policies. Other things equal, therefore, we would not expect farmers to purchase any policy that covers only these tail ends of the agricultural season. There is a smaller (though still nontrivial) discount requirement for policies covering cropping from sowing to harvest (INR 1,000). In sum, though it seems farmers would not be interested in policies that protect against risks either leading up to or following the monsoon season, they also clearly perceive some risk of crop loss due to sources apart from just rainfall (whether deficiencies or excesses) which presumably would be covered by a policy covering the sowing to harvest period.

Farmers would demand a discount for insurance that assessed losses by remote sensing or rainfall indices, though the discount that would be demanded is not huge (roughly INR 400 for each of the two alternative methods). Farmers evidently prefer to have losses assessed by crop-cutting experiments conducted at the panchayat level, despite the fact that the costs for crop-cutting experiments make the insurance policies more expensive for the insured. While it is difficult to estimate the cost of conducting a crop-cutting experiment, and the costs will likely vary widely from state to state, we can roughly estimate the cost based on historical data. For example, we know that a crop-cutting experiment cost about INR 300 in 2004 (World Bank, 2007). Based on general inflation levels over the ensuing 14 years, this corresponds to a 2018 equivalent price of about INR 500 per crop-cutting experiment. This assumes that, for example, wages for the agricultural workers responsible for the crop cuts just keep up with the cost of living. For remotely sensed or index-based loss assessments, the variable costs are essentially nil. Consequently, the administrative loads on these types of policies would be considerably less, thereby lowering the cost of insurance – something that would clearly be attractive for farmers. Whether the reduction in farmers' price would exceed the discount they would demand due to a preference for crop-cutting experiments remains to be seen.

Farmers would be willing to pay substantially more for insurance if they could believe that payments would be timely. On average, farmers would be willing to pay a premium of over INR 1,000 if indemnity payments would be guaranteed within 6 weeks of the loss assessments. This is quite important, and has implications for the ultimate design of improved crop insurance policies.

One of the primary concerns that has arisen with regards to assessing losses by crop-cutting experiments is that these can take a long time and lead to delayed indemnification. Other methods for assessing losses (e.g., by remote sensing or based on parametric weather indices) can facilitate much more rapid payment deliveries.

5.2 Correlated WTP parameters

As previously discussed, column (2) in Table 3 reports WTPs allowing for preferences for the different policy attributes to be correlated.

Table 4 reports the covariance, correlation, and Cholesky (lower) decomposition matrices that reflect these correlations. In particular, the correlation matrix provides details into how preferences co-move. For example, preferences for certain and timely indemnity payments are negatively correlated with preferences for all the other product features, except loss assessments via remote sensing. This correlation is not especially strong (0.127), but it is nonetheless interesting that increasing valuations for guaranteed, timely indemnity payments are positively correlated with insurance policy designs that increase the likelihood of timely payment delivery.

The Cholesky decomposition matrix provides information about the degree of variation directly attributable to the different attributes. The first element is simply the standard deviation for the random WTP coefficient associated with the sowing to harvesting coverage level. Subsequent diagonal elements represent the amount of variance attributable to random WTP coefficients once the correlations with the other coefficients have been removed. The off-diagonal elements represent the amount of cross-coefficient correlation that was previously confounded with standard deviations for models not controlling for these correlations (Hensher et al., 2005). For example, the amount of variance directly attributable to the indemnity payment timing random WTP coefficient is not 0.767, as would be suggested based on just examining the standard deviation of the WTP distribution (from Table 3), but is really 0.645: there are negative portions due to negative correlations with the various coverage periods, loss assessments from weather indices, and sum insured that would otherwise be confounded within the standard deviation estimate if the correlation were not accounted for.

5.3 Attribute non-attendance

In addition to controlling for correlated preferences, it may also be useful to consider the salience of the different attributes when respondents are evaluating choice scenarios. To evaluate this, we consider inferred attribute non-attendance using the method proposed by Hess & Hensher (2010). We use the individual-level estimates of the WTP distributions for the various insurance policy attributes, and compare the variation in individual WTP estimates relative to the expected WTP level. Specifically, we compute a noise-to-signal ratio by dividing the standard deviation of the WTP distribution by the mean WTP for each individual and for each policy attribute.

Table 5 reports the proportion of respondents in the sample who were deemed to have ignored the different insurance policy attributes based on this procedure. Most of the insurance policy features appear to be quite strongly attended to. Fewer than 5 percent of respondents appear to have ignored the timing of indemnity payments, and virtually no one appears to have ignored the sum insured – obviously an important feature of any insurance policy. Interestingly, there are mixed results when it comes to the coverage period. Nearly 25 percent of respondents appear to have ignored the coverage period if it covered the sowing to harvest period, but almost no one appears to have ignored the coverage period if it was either only the pre-sowing period or only the post-harvest period. For those that ignore the sowing to harvest coverage period, we can infer that they essentially view the policy as indistinguishable from one that covered the full pre-sowing to post-harvest period (like those policies offered under PMFBY) and would therefore not demand a discount on the purchase of such a policy. A similar phenomenon arises for the alternative methods of loss assessment. Nearly 25 percent of respondents ignored each of the two alternative loss assessment methods. It might be tempting to suspect that these respondents are just not paying attention to the method with which losses are assessed, but this is not entirely accurate. There is essentially no correlation between respondents' behavior when it comes to attending to or ignoring these two loss assessment methods. In other words, rarely are those that ignored loss assessments via remote sensing the same individuals who ignored loss assessments via weather-based indices. Regardless, if we also infer that individuals view these loss assessment methods as indistinguishable from crop-cutting experiments, then this might further strengthen arguments for moving from expensive and time-consuming – not to mention rather subjective and opaque – crop-cutting experiments to other methods of loss assessment that are more economical and can facilitate more rapid indemnity payments.

5.4 Determinants of WTP

Using the individual-level conditional estimates of WTP, we next aim to isolate any systematic correlates of farmers' WTP for the difference insurance policy attributes. In so doing, we assume that attribute non-attendance (as defined above) indicates that the farmer would neither be willing to pay a premium nor demand a discount for the policy feature vis-à-vis the status quo policy.

Table 6 gives the estimates of the OLS regressions of individual WTP for various attributes as a function of various household characteristics. Each column pertains to the regression for the WTP of the different insurance policy attributes. By and large, the results do not suggest much in the way of systematic determinants of WTP for the insurance policy features considered in the present study, perhaps confirming the old adage *de gustibus non est disputandum*.[4] Where there are some interesting and statistically significant effects that emerge are in regards to WTP for insurance policies with alternative methods of loss assessments. In particular, there are interesting results that emerge based on farmers primary crop. We find that farmers who primarily cultivate rice during the monsoon season have a significantly higher WTP for insurance policies with loss assessments based on remote sensing (vis-à-vis farmers who primarily cultivate non-cereals during the monsoon season). This is a promising result, given that there have already been researchers and development practitioners working on the ground in India and other countries (largely in southeastern Asia) piloting remote sensing for rice yield prediction to eventually inform crop insurance programs.[5] The predictive accuracy of the remote sensing technologies has been rather encouraging, with predictive accuracy ranging between 85 percent and 96 percent across three sites in Tamil Nadu, India when predictions were made at the block (sub-district administrative

[4] This Latin phrase literally translates as "In matters tastes, there can be no dispute," but is often paraphrased as "There is no accounting for tastes."

[5] A prominent example is the Remote sensing-based Information and Insurance for Crops in Emerging Economies (RIICE) project, funded by the German Development Corporation (GIZ) and the Swiss Agency for Development and Cooperation, and led by the International Rice Research Institute (IRRI) in collaboration with Sarmap and SwissRe.

unit), compared with accuracy of 87 percent when predictions were made at the district level (Pazhanivelan et al., 2015). Other recent research has found remote sensing yield prediction accuracy in rice as high as 95 percent in China (Huang et al., 2013). The high spatial resolution and high – and increasing – predictive accuracy of these remote sensing technologies is a promising development, and the preeminence of rice cultivation across much of India would suggest a nascent market for such products.

We also found that farmers who primarily cultivate maize during the monsoon season have a significantly lower WTP for insurance policies with loss assessments based on weather indices (vis-à-vis farmers who primarily cultivate non-cereals during the monsoon season). Interestingly, 369 out of the total 372 farmers who primarily cultivate maize during the monsoon season are from Himachal Pradesh, a state with very large climatic variations due to differences in altitude. These large variations in climate conditions may increase the likelihood that realized weather conditions on a farmer's field may not match the realized weather conditions at the location where the weather data comprising the index are collected, thus increasing the basis risk that insured farmers could be exposed to. This may be one of the primary reasons why maize farmers may dislike index-based loss assessments.

Finally, we find evidence of a U-shaped relationship between cultivated area and farmers' WTP for crop insurance policies with loss assessments based on remote sensing technologies. Initially, WTP for crop insurance based on remote sensing is declining with increasing cultivated area, but begins to increase after farm sizes exceed nearly 43 acres. There are a couple of caveats that should be considered before placing too much emphasis on this result. First, the linear area effect is not statistically significant at conventional levels, so there may not be the initial negative relationship between area and WTP. Second, very few households in our sample – and, indeed throughout much of India – cultivate areas in excess of 43 acres. Consequently, the observed relationship may be a mere statistical aberration that should not likely have any bearing on actual agricultural policy.

6. Discussion

The results above would suggest that, other things equal, farmers would generally be interested in purchasing crop insurance similar to the products being offered under PMFBY, and furthermore at premium rates higher than they are currently being asked to pay. If that is indeed the case, then it is puzzling that crop insurance coverage remains so low in India, and seems to be declining. Recent reports suggest that gross cropped area covered by insurance policies under PMFBY fell by more than 20 percent, 59.55 million hectares in 2016-17 to 47.5 million hectares in 2017-18 (Business Standard, 2018). This remains less than 24 percent of gross cropped area in the country. At the same time, the number of insured farmers has also decreased by 14 percent, from 55 million to about 48 million. Related to the sluggish – and declining – enrollments, one of the major challenges that policymakers in India face regards the long time delay in delivering indemnity payments. There is also anecdotal evidence that insurance company representatives – who take part in the crop-cutting experiments – lower the threshold limit below which indemnities are issued, so that even farmers with substantial crop losses may not qualify for payment (Business Standard, 2018).

Even before these recent declines, only about one third of farmers in India were insured. One obvious reason for the lack of coverage is that many farmers simply do not know about this scheme. From our data, nearly 35 percent of farmers across these four states had never heard of PMFBY. Furthermore, because holding crop insurance is typically compulsory for farmers accessing loans, there is evidence that insurance companies do not consider non-loanee farmers to be profitable (IIMA, 2018). There is also evidence that significant transaction costs hinder the broad uptake of crop insurance in India. These transaction costs arise not only in acquiring insurance, but also in filing claims. For example, farmers may have to travel several kilometers to reach the nearest financial institution. From our data, roughly 10 percent of farmers indicated that they would not likely purchase insurance if they had to travel far to submit the requisite paperwork for acquiring insurance. Farmers are also required to submit sensitive personal details, such as Aadhar (unique identifier) numbers, bank account details, or land records. Not only would such requirements exclude farmers who do not have, for example, land title (e.g., tenant or sharecropping farmers), but many farmers are evidently sensitive to sharing this information. From our data, roughly 8 percent of farmers would be unlikely to purchase insurance if they had to submit their Aadhar details; 19 percent of farmers would be unlikely to purchase insurance if they had to submit their bank account details; and 20 percent of farmers would be unlikely to purchase insurance if they had to submit a copy of their land records. Many farmers are also averse to having to file insurance claims in-person. Over 14 percent of farmers in our sample indicated that they would be unlikely to purchase insurance if they had to personally inform the insurer of losses.

How can this ambitious government policy be amended to increase coverage rates and better meet the needs of Indian farmers. Clearly, the most pressing need is to expedite the delivery of indemnity payments. But it seems unrealistic to expect this to be implemented without concomitant changes to the way in which agricultural losses are assessed. The time associated with undertaking the requisite number of crop cutting experiments, not to mention the un-scientific manner in which these experiments are conducted – which, in turn, diminishes the external validity of the yield estimates based on the experiments – makes it incredibly difficult to process and distribute accurate indemnity payments (IIMA, 2018).[6] Assessing crop losses via other means, such as remote sensing technologies or weather-based indices, provide a means for more rapidly assessing crop damages, which in turn should facilitate more timely processing of indemnity payments.

How would insurance demand and farmer welfare change as the result of such a transition. Figure 3 plots empirical demand curves for two crop insurance products: a base policy similar to those being offered under PMFBY, and an alternative policy that has been modified so that losses are assessed via remote sensing, but also one that offers a guarantee that indemnity payments will be delivered within six weeks of the losses being detected. The horizontal axis depicts the percentage of cultivated area covered (or not) under crop insurance. Consequently, at any point at which the demand curve for the alternative policy is above the demand curve for the base policy, we would expect a higher proportion of cultivated area to be insured at a given price. For virtually all prices above INR 1,800 per hectare (representative of a 6 percent premium on an insured sum of INR 30,000 per hectare), demand for the alternative policy exceeds demand for the base policy. For example, at a price of INR 2,100 per hectare (representative of a 7 percent premium on an insured sum of INR 30,000 per hectare), we would expect roughly 46 percent of cultivated area to be insured under the alternative policy, but only 43 percent of cultivated area to be insured under the

[6] IIMA (2018) estimates that between 1,500,000 and 2,000,000 crop cutting exercises are required each season. The report finds that these crop cutting experiments are "highly ill-managed" and "prone to human error and manipulation."

base policy. This may not seem like a large margin, but achieving 46 percent coverage of cultivated area is a marked improvement on the existing achievements under PMFBY.

Perhaps it is more appropriate not to compare demand at the same price, but to consider demand at different cost structures, but for example, under comparable insurance company profit margins. While these data are not readily available, we can be quite certain that the farmers' cost for the alternative policy would be considerably less than their cost for the base policy in order to secure insurance companies the same profit margin, since the firms' administrative costs (most notably associated with loss assessments and reinsurance) would be considerably lower under the alternative policy. By extension, the price they would need to charge to maintain the same profit margins that they earn under the base policy would also be considerably lower. The welfare effects of this would be sizeable, reflected in the twofold impacts of an increased insured area and a reduction in the cost of insurance for those who would already otherwise be insured.

7. Conclusion

This study explores Indian farmers' demand for crop insurance, particularly in light of the much-hyped and highly ambitious Pradhan Mantri Fasal Bima Yojana (PMFBY). While India has a long history with crop insurance, the level of farmers insured under various government programs has remained disappointingly low. Prime Minister Modi's PMFBY scheme is meant to improve upon some of the previous failed programs and aims to increase the area under crop insurance to as much as 50 percent of the gross cropped area in the country. Yet despite subsidies in excess of 75 percent, the level of insurance take-up has been slower than anticipated, and has actually declined in recent years. Arguably, one of the reasons why insurance demand has been so sluggish is that policies are rarely designed with the farmers in mind.

Our study aims to fill this knowledge gap by assessing farmers' preferences for various crop insurance features, with the objective of optimizing the design of crop insurance to satisfy farmers' needs. To address this, we employed a discrete choice experiment with a sample of farmers from four Indian states (Gujarat, Himachal Pradesh, Karnataka, and Uttar Pradesh). By re-parameterizing the random utility model that underlies farmers' decision making in the experiment, we are able to directly estimate farmers' WTP for various insurance product attributes allowing for preference and scale heterogeneity and without imposing unrealistic restrictions on farmers' sensitivity to insurance premiums.

Our results suggest that farmers are generally willing to pay considerably more – nearly five times more – for crop insurance than they are asked to pay under PMFBY (a 10 percent premium on the sum insured versus a 2 percent premium on the sum insured). While farmers prefer loss assessments through crop cutting experiments, they also have a very strong preference for assurances that indemnities will be paid in a timely fashion (e.g., within 6 weeks of the loss assessment). Unfortunately, in this regard, farmers generally cannot have their cake and eat it too: the myriad challenges associated with the completion of 1.5 – 2 million crop cutting experiments nationwide lead to significant delays in the delivery of payments. Other methods of loss assessment – such as relying on remote sensing technologies or basing payouts on a weather index – can facilitate much more rapid delivery of indemnities, and can reduce insurance companies' marginal costs to basically zero. Yet farmers are at least initially wary of these rather intangible method for loss assessments, and consequently would require a discount on their premiums to be enticed to purchase.

When we consider the transition from the status quo variety of crop insurance to an alternative policy that incorporates assessment of losses via remote sensing with guaranteed payment of indemnities in a timely fashion, we find that there are significant welfare gains to farmers, especially if we consider the lower cost of insurance that could result from eliminating the need for crop cutting experiments. While we are not able to directly estimate the magnitude of these welfare effects on a national basis, we can easily qualify or characterize these impacts. First, even when we abstract from cost considerations, the excess value that is associated with the alternative policy vis-à-vis the base policy structure (i.e., total difference in area under the demand curves) is significant. When there is a change in the cost of insurance (which we assume because of the reduction in insurers' costs due to eliminating the need for crop cutting experiments), there are two effects: the increase in cropped area (which presumably translates into a more-or-less proportional increase in the number of insured farmers), and the increased surplus experienced by farmers that would already be insured now paying a lower price. Finally, to the extent that the higher WTP and lower cost of this alternative policy structure reduces the need for government subsidies, there is a reduction in the marginal excess tax burden needed to finance these subsidies.

This study points to several avenues for future research. For starters, researchers or policymakers may wish to expand upon the choice experiment design used in the present study to consider other insurance product attributes. The attributes considered in the present study were thought to be the most salient in farmers decision-making, but admittedly any choice experiment design requires simplification and subjectivity. In addition, because there is no financial recourse for decisions made in the course of a choice experiment such as this, there is the potential for hypothetical bias to inflate the estimated WTP relative to what farmers actually would pay if they were to engage in actual insurance markets. This is a common criticism of choice experiments, though some authors have argued that the ability of such stated preference data to engender the estimation and prediction of real market behavior is comparable to those of revealed preference data (e.g., Louviere et al., 2000). Nevertheless, future research could consider other valuation elicitation methods that might be more immune to such potential for bias. The findings from this study and any future research could be very valuable for the design of alternative crop insurance products that could be piloted in an experimental setting. Piloting insurance programs with alternative crop insurance designs would provide more concrete insight into the potential for modified insurance products to increase the number of insured farmers and the total cultivated area insured.

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Table 1. Attributes and attribute levels included in discrete choice experiment

Attribute	**Levels**			
Coverage period	Pre-sowing to post-harvest	Sowing to harvest	Pre-sowing only	Post-harvest only
Method of loss assessment	Crop-cutting experiment at village/panchayat	Remote-sensing (satellite) based metric	Rainfall-based index (pays out if rainfall less than 75 percent of historical average)	
Timing of insurance payments	Within six weeks of loss assessment (100 percent guaranteed)	50 percent change of payment within six weeks; 50 percent chance payment more than 6 months delayed		
Insured sum	INR 20,000 per hectare	INR 30,000 per hectare	INR 40,000 per hectare	
Premium	2.5 percent of insured sum	4 percent of insured sum	10 percent of insured sum	

Note: When choice sets were presented to survey participants, insured sum was converted to a monetary sum per acre of land (as opposed to per hectare), while premium was converted to a monetary amount by multiplying the premium rate by the insured sum. Choice cards were translated from English into local languages (Gujarati, Kannada, or Hindi)

Table 2. Descriptive statistics of sample households

	Full Sample	Gujarat	Himachal Pradesh	Karnataka	Uttar Pradesh
Age	47.84 (0.54)	51.69 (1.02)	48.04 (1.08)	43.81 (1.05)	47.83 (1.10)
Gender (proportion male)	0.86 (0.01)	1.00 –	0.59 (0.04)	0.89 (0.03)	0.97 (0.01)
Farming experience	24.55 (0.57)	26.09 (1.16)	25.86 (1.19)	21.39 (1.02)	24.84 (1.11)
General caste (proportion)	0.50 (0.02)	0.70 (0.04)	0.74 (0.04)	0.30 (0.04)	0.24 (0.04)
Other backward class (proportion)	0.34 (0.02)	0.20 (0.03)	0.04 (0.02)	0.42 (0.04)	0.68 (0.04)
Scheduled tribe/Scheduled caste (SC/ST; proportion)	0.16 (0.02)	0.10 (0.03)	0.22 (0.03)	0.25 (0.04)	0.08 (0.02)
Area cultivated during monsoon season 2017 (acres)	5.39 (0.31)	9.61 (0.71)	2.25 (0.29)	6.43 (0.85)	3.32 (0.24)
Total grain harvested during monsoon season 2017 (kg)	4987.81 (531.65)	8824.93 (1522.22)	1433.64 (497.27)	6218.35 (1307.41)	3544.72 (325.54)
Primary monsoon season crop is rice (proportion)	0.70 (0.02)	0.94 (0.02)	0.01 (0.01)	0.85 (0.03)	1.00 0.00
Primary monsoon season crop is maize (proportion)	0.22 (0.02)	0.00 0.00	0.85 (0.03)	0.01 (0.01)	0.00 0.00
Duration of primary crop from sowing to harvest (months)	3.99 (0.04)	4.12 (0.06)	3.53 (0.07)	4.75 (0.09)	3.56 (0.05)
Insured during monsoon season 2017 (proportion)	0.11 (0.01)	0.11 (0.03)	0.06 (0.02)	0.14 (0.03)	0.14 (0.03)
Insured during monsoon season 2017 because accessed credit (proportion)	0.09 (0.01)	0.11 (0.03)	0.06 (0.02)	0.08 (0.02)	0.12 (0.03)
Number of observations	572	142	144	142	144

Note: Standard errors in parentheses.

Table 3. Willingness-to-pay estimates from discrete choice experiment

	(1) Uncorrelated	(2) Correlated
Willingness-to-pay estimates		
Coverage level: sowing to harvest	-1.004***	-0.977***
	(0.188)	(0.202)
Coverage level: pre-sowing	-5.225***	-5.004***
	(0.522)	(0.474)
Coverage level: post-harvest	-5.072***	-4.807***
	(0.464)	(0.411)
Loss assessment: remote sensing	-0.391*	-0.435*
	(0.194)	(0.194)
Loss assessment: rainfall index	-0.237	-0.433*
	(0.195)	(0.196)
Timing: guaranteed within 6 weeks	0.992***	1.014***
	(0.163)	(0.165)
Sum insured (INR 1,000)	0.107***	0.098***
	(0.009)	(0.009)
Distributions of willingness-to-pay		
SD(Coverage level: sowing to harvest)	1.445***	2.213***
	(0.372)	(0.314)
SD(Coverage level: pre-sowing)	3.149***	3.792***
	(0.41)	(0.401)
SD(Coverage level: post-harvest)	2.122***	3.485***
	(0.488)	(0.396)
SD(Loss assessment: remote sensing)	1.897***	2.061***
	(0.263)	(0.24)
SD(Loss assessment: rainfall index)	1.784***	2.140***
	(0.313)	(0.258)
SD(Timing: guaranteed within 6 weeks)	0.242	0.767*
	(0.816)	(0.351)
SD(Sum insured (INR 1,000))	0.020	0.054***
	(0.031)	(0.015)
SD(Scale parameter)	1.041***	1.152***
	(0.141)	(0.163)
Number of choice observations	3,432	3,432
Number of choice sets per individual	6	6
Number of individuals	572	572
Log-likelihood function value	-3,073.50	-3,041.00
Number of iterations	71	187
Number of Halton draws used in simulation	1,000	1,000

Note: *** Significant at 1 percent level; ** Significant at 5 percent level; * Significant at 10 percent level. Standard errors in parentheses.

Table 4. Covariance, correlation, and Cholesky decomposition matrices from generalized mixed logit estimation permitting free correlation in WTP parameters

				Covariance matrix			
	Cov$_1$	Cov$_2$	Cov$_3$	Loss$_1$	Loss$_2$	Timing	Sum
Cov$_1$	***4.897***	***4.111***	***5.526***	**1.368**	***2.454***	-0.386	0.006
Cov$_2$	***4.111***	***14.377***	***9.576***	-1.312	***3.172***	*-1.466*	-0.050
Cov$_3$	***5.526***	***9.576***	***12.147***	0.307	***4.152***	-1.006	**-0.089**
Loss$_1$	**1.368**	-1.312	0.307	***4.249***	**1.299**	0.201	-0.027
Loss$_2$	***2.454***	***3.172***	***4.152***	**1.299**	***4.581***	-0.548	-0.036
Timing	-0.386	*-1.466*	-1.006	0.201	-0.548	0.588	-0.008
Sum	0.006	-0.050	**-0.089**	-0.027	-0.036	-0.008	*0.003*
				Correlation matrix			
	Cov$_1$	Cov$_2$	Cov$_3$	Loss$_1$	Loss$_2$	Timing	Sum
Cov$_1$	1	0.490	0.716	0.300	0.518	-0.228	0.050
Cov$_2$	0.490	1	0.725	-0.168	0.391	-0.504	-0.244
Cov$_3$	0.716	0.725	1	0.043	0.557	-0.376	-0.470
Loss$_1$	0.300	-0.168	0.043	1	0.295	0.127	-0.238
Loss$_2$	0.518	0.391	0.557	0.295	1	-0.334	-0.313
Timing	-0.228	-0.504	-0.376	0.127	-0.334	1	-0.185
Sum	0.050	-0.244	-0.470	-0.238	-0.313	-0.185	1
				Cholesky Decomposition Matrix			
	Cov$_1$	Cov$_2$	Cov$_3$	Loss$_1$	Loss$_2$	Timing	Sum
Cov$_1$	***2.213***	0	0	0	0	0	0
Cov$_2$	***1.858***	***3.305***	0	0	0	0	0
Cov$_3$	***2.497***	***1.494***	***1.919***	0	0	0	0
Loss$_1$	**0.618**	***-0.745***	-0.065	***1.819***	0	0	0
Loss$_2$	***1.109***	0.336	0.459	*0.492*	***1.669***	0	0
Timing	-0.174	-0.346	-0.028	0.027	-0.143	*0.645*	0
Sum	0.003	-0.017	***-0.037***	*-0.024*	-0.003	-0.022	0.016

Note: Italicized figures are statistically significant at the 10 percent level; bold figures are statistically significant at the 5 percent level; bold and italicized figures are statistically significant at the 1 percent level.

Table 5. Non-attendance to insurance policy attributes

Insurance policy attribute	Proportion ignoring attribute
Coverage level: sowing to harvest	0.224
Coverage level: pre-sowing	0.033
Coverage level: post-harvest	0.014
Loss assessment: remote sensing	0.268
Loss assessment: rainfall index	0.236
Timing: guaranteed within 6 weeks	0.054
Sum insured (INR 1,000)	0.014

Note: Respondents are deemed to have ignored the insurance policy attribute if the noise-to-signal ratio from the respondents' WTP distribution is greater than 2 (Hess & Hensher, 2010).

Table 6. Determinants of willingness to pay for insurance contract attributes

Dependent variable: WTP for:	(1) Coverage period: Sowing to harvest	(2) Coverage period: Pre-sowing	(3) Coverage period: Post harvest	(4) Loss assessment: Remote sensing	(5) Loss assessment: Weather index	(6) Timely delivery of indemnity payments	(7) Sum insured (INR 1,000)
Intercept	-1.885*	-6.168**	-4.959**	-0.915	-0.221	1.196***	0.079**
	(1.026)	(2.416)	(2.276)	(0.871)	(0.920)	(0.417)	(0.038)
Gender (male = 1)	0.421**	0.482	0.748	0.122	0.242	-0.016	-0.008
	(0.212)	(0.499)	(0.470)	(0.180)	(0.190)	(0.086)	(0.008)
Age (yrs)	0.022	-0.013	-0.047	0.003	-0.026	-0.002	0.002
	(0.044)	(0.105)	(0.099)	(0.038)	(0.040)	(0.018)	(0.002)
Age^2 (×1,000)	-0.024	0.518	0.797	0.054	0.343	-0.024	-0.023
	(0.446)	(1.051)	(0.990)	(0.379)	(0.400)	(0.181)	(0.017)
Experience (yrs)	-0.032	-0.010	-0.009	-0.020	-0.023	0.005	-0.001
	(0.024)	(0.057)	(0.053)	(0.020)	(0.022)	(0.010)	(0.001)
$Experience^2$	0.299	-0.595	-0.447	0.251	0.330	-0.005	0.020
(×1,000)	(0.413)	(0.972)	(0.916)	(0.351)	(0.370)	(0.168)	(0.015)
Area cultivated	-0.013	0.024	-0.016	-0.028	0.006	-0.004	0.000
(acres)	(0.022)	(0.051)	(0.048)	(0.018)	(0.019)	(0.009)	(0.001)
Area $cultivated^2$	-0.053	-1.482	-0.538	0.669*	-0.259	0.270	0.007
(×1,000)	(0.473)	(1.114)	(1.050)	(0.402)	(0.424)	(0.192)	(0.018)
Primary crop:	0.215	0.569	0.454	0.493*	0.193	-0.141	-0.007
Rice	(0.298)	(0.701)	(0.660)	(0.253)	(0.267)	(0.121)	(0.011)
Primary crop:	-0.270	-0.758	-0.934	0.330	-0.614**	0.180	0.008
Maize	(0.348)	(0.818)	(0.771)	(0.295)	(0.311)	(0.141)	(0.013)
Crop duration	0.006	0.099	0.067	-0.008	0.004	-0.019	-0.003
(days)	(0.076)	(0.178)	(0.168)	(0.064)	(0.068)	(0.031)	(0.003)
Insured (=1)	-0.002	0.622	0.401	0.014	0.075	-0.098	-0.011
	(0.202)	(0.474)	(0.447)	(0.171)	(0.181)	(0.082)	(0.008)
Other backward	-0.076	-0.353	-0.153	0.052	-0.105	0.025	0.000
caste (OBC)	(0.166)	(0.391)	(0.368)	(0.141)	(0.149)	(0.067)	(0.006)
Scheduled	0.103	0.413	0.385	0.010	0.051	-0.085	-0.006
caste/scheduled tribe (SC/ST)	(0.189)	(0.444)	(0.419)	(0.160)	(0.169)	(0.077)	(0.007)
R2	0.031	0.068	0.058	0.001	0.015	0.054	0.028
Number of observations	572	572	572	572	572	572	572

Note: *** Significant at 1 percent level; ** Significant at 5 percent level; * Significant at 10 percent level. Standard errors in parentheses. Each regression controls for state level fixed effects. Dependent variable in each regression is the conditional mean (marginal) WTP for each of the insurance policy characteristics estimated by the generalized multinomial logit regression (see Table 3), adjusted for inferred attribute non-attendance (see

Table 5).

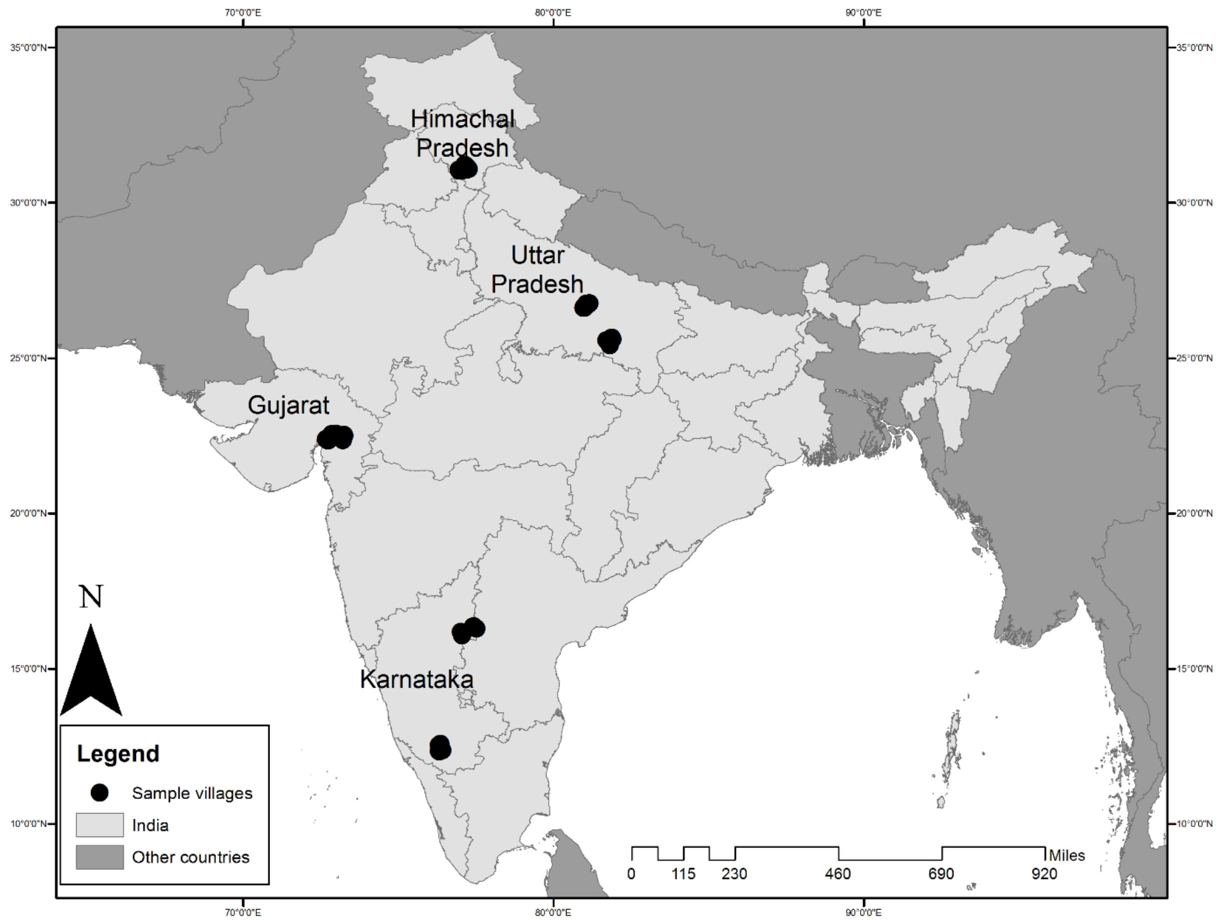

Figure 1. Sample areas

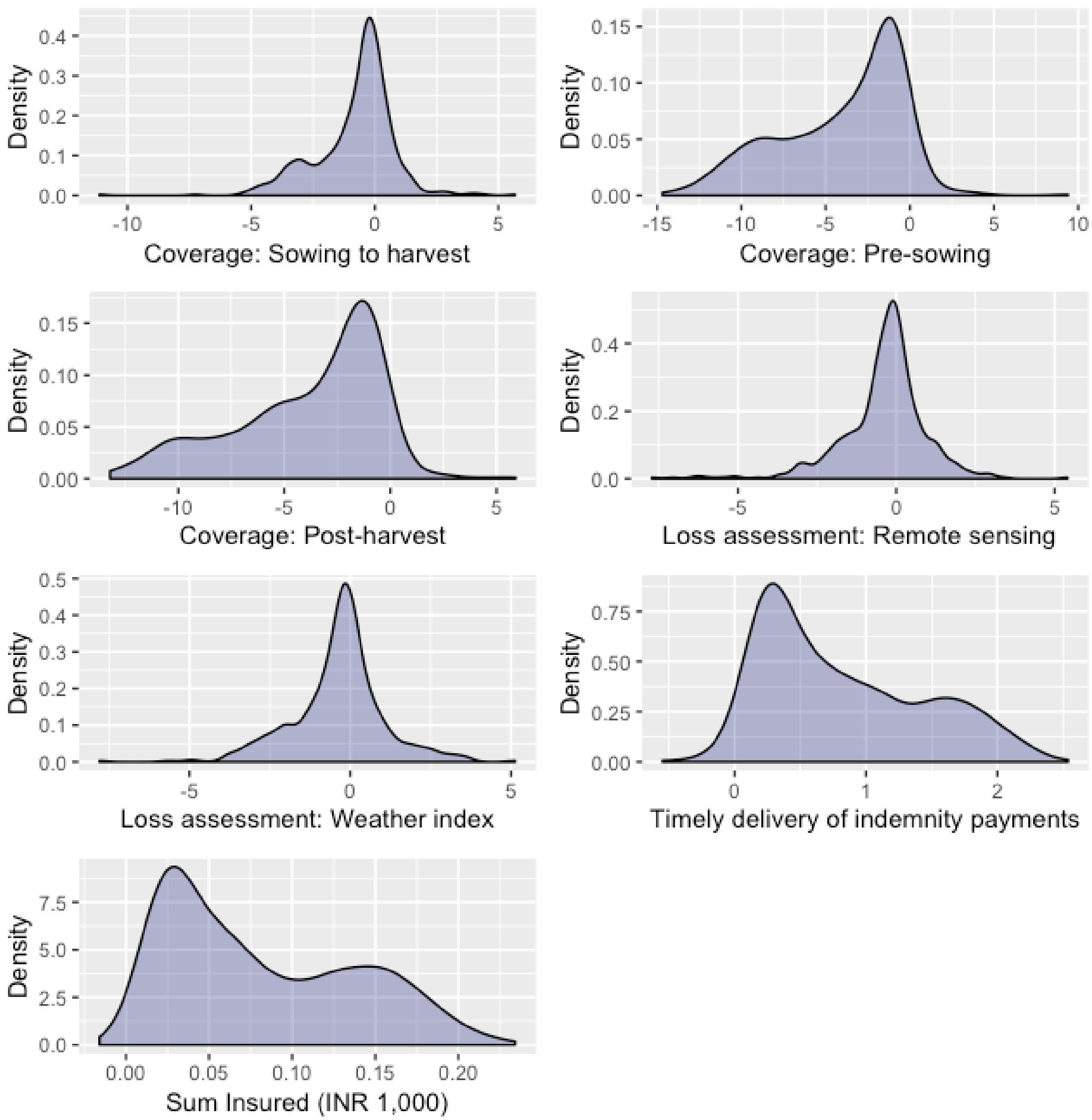

Figure 2. Empirical distributions of WTP for various insurance policy attributes

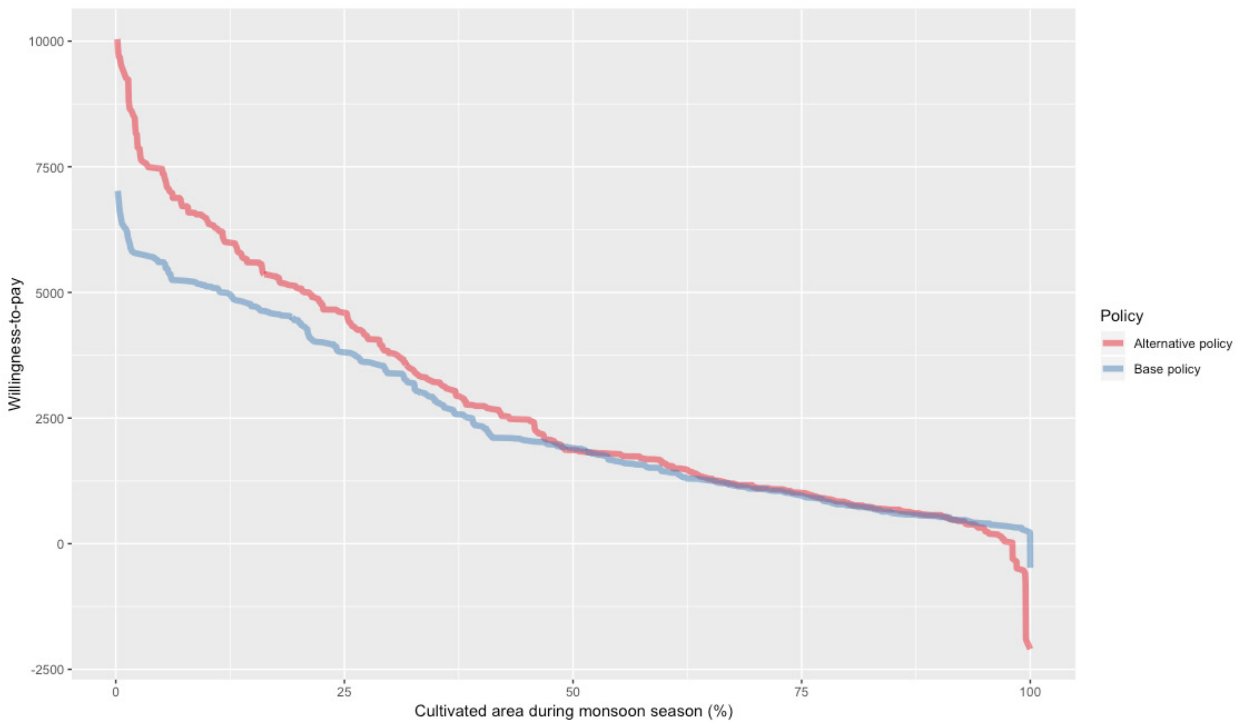

Figure 3. Demand curves for competing crop insurance packages: Base policy similar to those offered under PMFBY versus alternative policy offering more timely delivery of indemnity payments under remote sensing

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