Demand for Crop Insurance: Evidence from Pakistan*

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Abstract

Smallholder farmers are disproportionately vulnerable to climate risk. While crop insurance can help protect farmers against climate damages, its uptake remains low across both high-income and developing countries. This puzzle is often attributed to a mix of information frictions, liquidity constraints, limited trust, and basis risk—the mismatch between payouts and actual losses. We conduct a field experiment across more than 100 villages in Punjab, Pakistan, eliciting willingness to pay for three index insurance contracts that vary in basis risk. We find that willingness to pay declines with coarser index areas: moving from individual- to district-level indices reduces willingness to pay by approximately 10%. A randomized information intervention correcting beliefs about historical rainfall and temperature modestly increases WTP and significantly raises the perceived likelihood of insurance payout, reducing the wedge between expected payout and WTP by 23% on average. To interpret these findings, we develop a structural model of crop insurance demand, incorporating farmer-specific beliefs and contract-level basis risk. Estimating the model using experimentally elicited utility parameters allows us to recover welfare-relevant demand curves free from behavioral frictions and quantify how much basis risk and misperceptions suppress insurance uptake.

Keywords: Adaptation; agriculture; climate; insurance

JEL Classification: D25; D81; O12; O13; Q12; Q54

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1 Introduction

Over 60% of the Pakistani population resides in rural areas, where agriculture serves as their primary source of income and employment. Farmers encounter various risks throughout the agricultural production process, with yield fluctuations being among the most significant challenges. In anticipation to these shocks, farmers can adapt both within and across seasons by adjusting their input choices, planting schedules, or crop choice based on their understanding of climatic conditions (Carleton et al., 2024). If these shocks are individual-specific, farmers may mitigate consumption fluctuations by leveraging existing communal networks and markets (Kochar, 1999). However, for more frequent, spatially correlated, and catastrophic shocks—a common feature of climate change—current adaptation strategies, including reliance on local or informal networks, may be inadequate to safeguard the livelihoods of small-scale farmers.

Typically, these correlated risks can be mitigated through insurance that pays out in the event of extreme weather occurrences or yield losses, thereby minimizing income uncertainty and incentivizing investments in productive technologies. However, the value placed by individuals on crop insurance remains consistently low, and the demand for insurance products continues to be limited in several settings (Carter et al., 2016, 2017; Cole and Xiong, 2017), despite the limited success of initiatives aimed at providing information, subsidies, and increasing trust (Cai et al., 2020). Frequently, the insurance contracts available in developing countries take the form of index insurance, which may be based on weather (e.g., rainfall) or yields (Carter et al., 2017). These index contracts are relatively easier to implement in data-poor countries and largely mitigate moral hazard concerns. One major drawback of such contracts include its inherent basis risk, i.e., the mismatch between individual and index losses. Emerging theoretical and empirical literature suggests this latter contract feature is a significant barrier to the uptake of crop index insurance (Clarke, 2016; Cole et al., 2013). However, there is limited evidence on the financial amount that farmers are willing to forego to reduce the basis risk associated with these contracts.

We conduct a cluster-randomized controlled trial in 101 villages in the province of Punjab, involving up to 2,065 farm households, to examine farmers' willingness to pay (WTP) for crop insurance, and the factors that influence their demand for crop insurance, including basis risk and weather information. The sample was drawn from 11 districts and 22 subdistricts (*tehsils*) between November and December 2024, which coincide with the planting phase of the Rabi 2024-25 season. We focus our study on Punjab for two main reasons. First, Punjab is one of the key agricultural production and consumption hubs of the country; and second, it is the only province in Pakistan to have had a formal crop insurance program, the Punjab Crop Insurance Program, which started in 2017 and ended in 2025. Under this program, the take-up rate was almost zero unless crop insurance was provided for free. Therefore, understanding the factors that influence demand is essential for redesigning the crop insurance program in the province.

Our survey includes a comprehensive range of questions about household demographics, agricultural production, consumption, household assets, farm assets, and livestock. There are three key novel sections in our survey. First, we elicit subjective distributions regarding beliefs about past, present, and future temperature and rainfall patterns, as well as farmers' perceived correlation between weather and yield. This section helps us understand how beliefs and information about weather influence decision-making. Second, we inquire about insurance in general and the history of insurance before progressing to four rounds of bidding games. We elicit farmers' WTP using multiple price listings for three average-yield index insurance contracts. These contracts were designed so that the payout coverage remain fixed, while the scale at which claims were triggered varied based on (i) district, (ii) tehsil, and (iii) individual. This allows us to assess how much farmers are willing to pay for three different contracts, which vary by the area covered in the index, to be interpreted as a measure for basis risk; that is, a larger area in the index implies higher basis risk. We also cross-randomize four price distributions at the farmer-contract level, which are used to determine the prices presented to each farmer for every contract, and randomly allocate half of the farmers within a village to have their prices displayed in ascending order, to mitigate anchoring effects. Third, we engage in four games with the farmers to recover utility parameters (risk, time, intertemporal substitution, and uncertainty aversion) in an incentive-compatible manner.

As part of our study, we also randomize the provision of weather information across villages to examine the role information plays in the demand for crop insurance and to isolate the true underlying stated preferences for insurance contracts. Half of the villages were randomly allocated to receiving the weather information, while the rest acted as control villages. Farmers in the treatment villages received weather information, including the number of rainy days and the average temperature during the Rabi season, which spans from October to March, over the past ten years in their sub-district. This information was provided after we gathered data on their subjective beliefs about past, present, and future climate conditions, but before eliciting their willingness to pay (WTP) for crop insurance.

We find that farmers are sensitive to the level of basis risk: moving from individual- to district-level indices reduces WTP by approximately 10%, consistent with declining payout correlation at broader spatial scales. Information frictions also play a significant role: providing accurate historical weather information increases both WTP and the subjective probability that the contract will trigger, and reduces the wedge between expected payouts and WTP by about 23%, suggesting that inaccurate beliefs distort stated preferences about crop insurance elicited through multiple price listings. These effects are stronger for farmers who initially underestimate weather volatility and those who better understand insurance. We also find that risk-averse individuals and those with lower intertemporal substitution value insurance more.

To interpret these patterns, we develop a structural model of insurance demand under Epstein-Zin preferences, incorporating subjective beliefs and contract-specific basis risk. The model formalizes how demand is shaped by both preference heterogeneity and the statistical properties of index design, and it allows us to recover welfare-relevant demand curves corrected for behavioral frictions.

A growing literature studies how households in developing countries adapt to climate change and the role of frictions and constraints in these responses (Carleton et al., 2024). A key theme in this work is that risk and credit constraints often inhibit efficient adaptation, motivating the development of new financial instruments such as agricultural insurance (Karlan et al., 2014) and contingent loan products (Lane, 2024). Alongside market constraints, information frictions and subjective beliefs critically shape adaptation behavior. Recent work shows that climate beliefs affect a range of agricultural decisions, including the timing of planting (Burlig et al., 2024), seed technology adoption (Patel, 2023), and irrigation (Zappalà, 2024). In this paper, we examine the role of behavioral frictions and incomplete information in shaping demand for index-based crop insurance. We use an experimental design that provides weather information to a random subset of villages prior to eliciting willingness to pay (WTP) for insurance contracts. Importantly, our structural model of insurance demand allows us to derive the welfare implications of inaccurate beliefs and to structurally recover behavioral parameters that mediate this response.

Despite considerable policy interest, demand for agricultural index insurance in developing countries remains persistently low (Carter et al., 2017). A large body of work has explored both price-related and behavioral explanations for this phenomenon. Liquidity constraints are a well-documented barrier: farmers often face competing demands for cash at the start of the planting season, which limits their ability to pay insurance premiums even when the product is actuarially fair (Cole et al., 2013; Karlan et al., 2014; Casaburi and Willis, 2018). Non-price frictions also play a central role. A lack of trust in insurers, limited financial education, and poor understanding of the insurance product all contribute to low demand, as does the absence of prior experience with payouts (Cole et al., 2013; Giné and Yang, 2009; Cai, 2016; Dercon et al., 2019; Cai et al., 2020). A third strand of the literature focuses on the design of insurance products themselves. A defining feature of index insurance is basis risk—the discrepancy between the index-triggered payout and a farmer's actual loss—which weakens the product's appeal (Clarke, 2016; Dercon et al., 2014; Hill et al., 2016; Jensen et al., 2016, 2018). While theory and evidence both indicate that higher basis risk reduces demand, few studies have been able to quantify farmers' valuation of this feature.

This paper makes three contributions to these literatures. First, it monetizes the value farmers place on reducing basis risk in the context of an area-yield index insurance product by varying the spatial resolution of the index. Second, it shows how beliefs about weather—elicited directly from farmers—shape willingness to pay, and how correcting these beliefs via information provision influences demand. Third, it structurally recovers preference parameters under Epstein-Zin preferences to disentangle the role of risk aversion, intertemporal substitution, and subjective beliefs in shaping insurance take-up. Together, these results offer new insight into how institutional and informational frictions jointly constrain climate adaptation.

The remainder of the paper is organized as follows. Section 2 presents the sample, research design, and data collection process. In Section 3, we provide empirical evidence on the factors driving crop insurance demand. Section 4 describes a structural model of crop insurance demand for climate adaptation and Section 5 describes the counterfactuals of the structural model that we will conduct.

2 Field Setting

This section delineates the sample, experimental design, and specifics of the data collected in the field study. Appendix Figure B1 summarizes our experimental design and timeline.

2.1 Sample

We conducted a cluster-randomized controlled trial in 101 villages in Punjab, Pakistan, covering up to 2,065 farm households, with the support of a local survey firm, between November, 21 and December, 20 2024.[1]. Households were selected only if they were growing or planned to grow any crops in Rabi 2024-25 and come from 22 tehsils (sub-districts) across 11 districts in Punjab, Pakistan.[2] These districts were randomly selected from those engaged in the agricultural production of one of the three main crops: wheat, rice, and cotton. For each district, we randomly selected two sub-districts based on (i) the presence of villages with at least 100 farm households engaged in agricultural production[3], and (ii) the implementing partner's assessment of safety for the enumerators to conduct surveys.[4] For most of the analysis, we restrict our primary sample to farmers who grew wheat (99.27% of the sample) as their main crop during the Rabi season 2024-25, which runs from October to March, and for those who wish to purchase crop insurance, even at no cost (i.e., for free) across all three contracts (explained in the subsection below). This restriction leaves us with a sample of 1,778 participants.[5]

The survey lasted approximately 45-60 minutes and included comprehensive questions about the agricultural activities of farmers during the last two growing seasons (Rabi 2023-24, Kharif 2024), the current season (Rabi 2024-25), and the upcoming growing season (Kharif 2025). We also collect detailed information about the primary crops grown during the Rabi season, and the Kharif season. Additionally, we included demographic and household-level questions covering education, age, household size, assets, income, consumption expenditures over the past 7 days, 30 days, and 5 months, savings, loans, farm plots, and livestock information. We also collected detailed insights on farmers' past, present, and future perceptions of climate and weather, as well as their understanding of the relationship between weather and crop yields.

2.2 Experimental Design

In this study, we aim to recover farmers' stated demand for crop insurance and identify factors that influence their hypothetical uptake. To achieve this, we collect detailed information on

[1]The survey activity was initially planned for the start of growing season in October 2024, but due to the political conditions in the country, including internet blackouts, the local partners advised delaying the field activity.

[2]Districts include: Bahawalnagar, Bahawalpur, Faisalabad, Gujranwala, Jhang, Khanewal, Layyah, Multan, Rahimyar Khan, Sheikhupura, and Vehari.

[3]This information was retrieved from the recent Mouza Census (2023).

[4]Enumerators reported certain areas to be dangerous due to ongoing conflicts between security forces and local insurgents.

[5]2,043 farmers grew wheat in Rabi 2024-25. Of those, 181 did not want to receive any crop insurance, even for free. For 84 farmers, we were unable to recover their willingness to pay using our first-switch strategy. We find this latter group to be balanced across all key demographic variables as our main sample.

agricultural production and practices, as well as the underlying climate beliefs that drive them, which enables us to investigate how exposure to extreme heat shocks impacts households and how farm households respond both within and across seasons.

To ascertain the demand for crop insurance, we elicit farmers' willingness to pay for three hypothetical index insurance contracts (explained in detail below). We utilize multiple price listings (similar to Becker-DeGroot-Marschak (BDM) (Becker et al., 1964)), in which farmers are sequentially presented with ten prices and asked whether they would be willing to purchase a specific insurance contract at that price. We derive their underlying WTP for a given contract based on their choices and the first switch.[6]

In our setting, farmers could choose between full insurance and no insurance (i.e., the number of contracts is fixed). Before asking farmers to bid on the insurance contracts, we conducted a practice round in which participants bid for a chocolate bar. This practice round was made incentive-compatible; that is, after it concluded, one of the options presented to the farmer was randomly selected and their choice implemented. If the farmer indicated they would buy at the price presented in that option, the chocolate was given to them, and the price was deducted from a credit of PKR 200 that we informed them they had access to (the price of chocolate never exceeded that amount). This exercise was also important for them to realize that each option is independent.

In each of the following rounds, we asked farmers about their willingness to pay (WTP) for the three insurance contracts, giving details about its coverage, PKR 30,000 per acre, which remained constant across all contracts, as well as the contract features, particularly the conditions under which claims would be triggered. With the assistance of the enumerators, respondents were asked about their WTP in PKR for each contract.

Farmers in each village were assigned to a two-stage price treatment arm. In the first stage, half of the farmers in a village were presented with prices in ascending order, while the other half were shown prices in descending order, to mitigate anchoring effects. In the second stage, farmers in a village were assigned to one of four price supports: $\mathcal{U}[0, 300], \mathcal{U}[300, 600], \mathcal{U}[600, 900]$, and $\mathcal{U}[900, 1200]$,[7] which was utilized to draw a random price p_{ic} for farmer i and contract c. For each farmer-contract pair, the first and last prices were either PKR 0 or PKR 1200, depending on whether they were in the ascending or descending arm. For farmers in ascending order, the first price shown to them was PKR 0, and the last price displayed would be PKR 1200. The random price, p_{ic}, along with the last price shown to the farmer, was then used to calculate the remaining eight prices by recovering the Δ_{ic}, which allowed movement from the random price p_{ic} to the last price in equal increments for a contract type c.

In addition to the price treatment, half of the villages were also assigned to a village-level information treatment, which we refer to as the 'weather' treatment. This involves providing information about the total number of rainy days (defined as days with strictly positive precipitation) and average temperatures over the last ten years in farmers' sub-districts during the Rabi season. We constructed this information from the ERA5-Land hourly climate reanalysis

[6]The results should be regarded as stated preferences since we did not make this exercise incentive-compatible.

[7]The price ranges were chosen based on the premium rates charged by insurance companies for wheat under the PCIP, even though the government fully subsidized it for the farmers.

data, which are available at an original spatial resolution of 0.1° ($\approx$ 11km). This information was communicated to farmers after we elicited their subjective probability distribution regarding weather and their understanding of its relationship to yield, but prior to eliciting their willingness to pay for insurance.

Finally, we elicit farmers' preferences regarding risk, time, intertemporal substitution, and uncertainty aversion in an incentive-compatible manner using the BDM method (Brown and Kim, 2014), allowing us to determine theoretical willingness to pay. Farmers were allocated a credit of PKR 200, from which the payment for an introductory game involving chocolate purchase to familiarize with BDM mechanism, alongside their earnings from the utility-parameter games, which had a minimum value of PKR 0. Payments were processed via mobile money on the same day, one week, or two weeks later, depending on the randomly selected outcomes from the games. We report sample descriptive statistics in Appendix Table B1.

2.2.1 Insurance Contracts

Farmers were invited to submit their bids for three hypothetical area-yield index insurance contracts, based on the existing insurance contract offered by the Government of Punjab under the Punjab Crop Insurance Program (PCIP).[8] The advantage of utilizing area-yield indices over the weather-based indices frequently discussed in the literature is that yield loss coverage addresses all types of risks farmers may encounter (weather, pests, floods, hailstorms, etc.). Similar to the PCIP contract, all three of our contracts offer the same coverage (PKR 30,000 per acre), and farmers were asked to choose either full insurance or none. The contracts we present differ by trigger. Specifically, they vary in the geographical area over which the index is computed, which acts as a proxy for basis risk (the larger the area, the higher the basis risk), while maintaining coverage constant. The triggers are as follows:

- *District* contract: Claims are triggered when the current average yield of the insured crop in the *district* falls at least 80% below the ten-year average yield of the insured crop in that *district*.
- *Tehsil* contract: Claims are triggered when the current average yield of the insured crop in the *tehsil* falls at least 80% below the ten-year average yield of the insured crop in that *tehsil*. This contract form is akin to the PCIP insurance contract.
- *Individual* contract: Claims are triggered when the current average yield of the insured crop in the *farmer's plot* falls at least 80% below the ten-year average yield of the insured crop in that *tehsil*.

As we transition from district-level to individual-level contracts, the index area decreases, enabling us to provide evidence of how index area influences farmers' willingness to pay. Furthermore, the indexed nature of our insurance contract will allow us to be less concerned about

[8] PCIP provided area-yield index insurance at the tehsil level and was in effect from Rabi 2017-18 until Rabi 2024-25, paying out PKR 30,000 per acre if the average yield of the tehsil fell below a pre-set historic average. As the government fully subsidized the insurance contracts, their supply was limited. Consequently, not all farmers had the opportunity to obtain one.

moral hazard, as individual decisions will have a reduced impact on triggering claims. Collusion at the sub-district or district level would require coordination among many farmers, which is likely to be minimal, given that numerous farmers operate independently on their small farms.

3 Motivating survey evidence

3.1 Demand for crop insurance

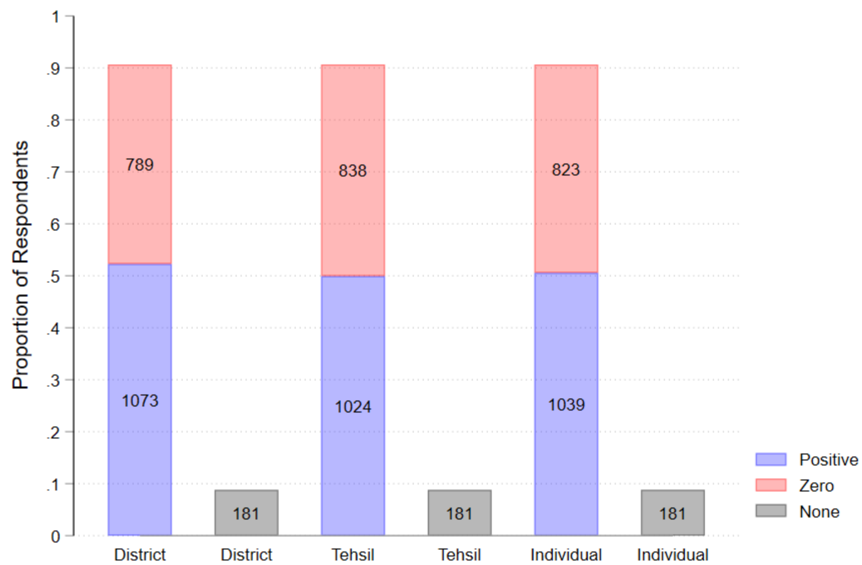
We elicit farmers' willingness to pay (WTP) for three index insurance contracts that vary by spatial coverage: district, sub-district (tehsil), or individual, using the Becker-DeGroot-Marschak method. After an incentive-compatible practice round with chocolate, each insurance contract was explained to the farmers one at a time, followed by ten questions about their willingness to accept the contract at the shown price, where the list of ten prices was drawn from one of the four price distributions.

Regardless of the type of contract, approximately 90% of the sample is willing to take crop insurance (Figure 1). About 51% of the sample is willing to pay a positive price for insurance, while 39% desires insurance, but only for free. The uptake in our setting is relatively higher than what is reported in the literature for comparable insurance contracts, which ranges from 5-20% (Cole et al., 2013). This however might be because of the hypothetical nature of the questions. Within our sample, only 10% of the farmers are not willing to insure against climate risk, even when provided for free. We ask these respondents the main reason against insurance even if free, and religion and trust appear to be the key reasons (Appendix Figure B2), in line with previous literature (Carter et al., 2017; Cole et al., 2013).

For farmers who exhibit a weakly positive demand for crop insurance, we plot the demand curve for the three different contract types in Figure 2. The raw inverse demand curves are broadly similar across contract types, with mass points at 0 and 1200—corresponding to the bounds of the price distribution. This clustering suggests limited differentiation among contracts, consistent with the absence of an active crop insurance market in this setting. Incomplete markets may leave farmers and their social networks with insufficient experience to interpret or value different contract features. Furthermore, variation in the supports of the offered price distributions may obscure systematic differences in demand. Appendix Figure B3 documents significant heterogeneity in WTP across farmers exposed to different price supports.

Most importantly, spatial coverage of the index (defined as the geographic area over which payouts are calculated) varies across contracts. In particular, individual-level insurance is defined over a farmer's own reported agricultural land, while tehsil- and district-level contracts aggregate over broader spatial units. We regress WTP on price support fixed effects and index spatial coverage to isolate remaining variation in preferences. The resulting residualized inverse demand curves, plotted in Figure 2b, reveal that while demand for district- and tehsil-level contracts remains similar, demand for individual-level insurance exhibits a pronounced hump. This indicates that, conditional on price support and spatial coverage, more farmers are willing to purchase individual-level coverage at a given residualized price. This suggests a stronger valuation of individual contracts, due to lower perceived basis risk.

Figure 1: Stated demand for crop insurance by contract type

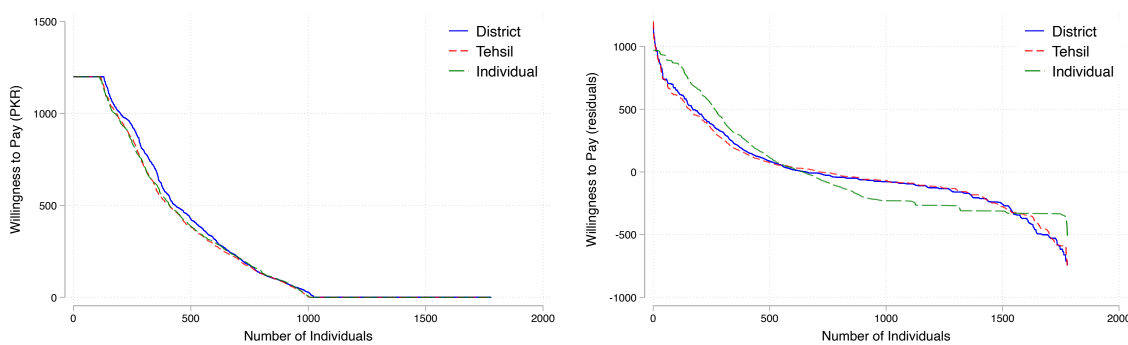


Notes: The figure shows willingness to pay for crop insurance across three different contracts (district, tehsil, and individual). The y-axis shows the proportion of respondents, while the number of respondents is displayed on each bar.

Figure 2: Inverse demand curve for crop insurance

(a) Willingness to Pay

(b) Willingness to Pay (Residuals)



Notes: Left-hand panel shows the inverse demand curve for the three different insurance contracts (district, tehsil, and individual). In the right-hand panel, we plot the residuals of the inverse demand curve for the three different insurance contracts (district, tehsil, and individual) once accounting for spatial area fixed effects for district and tehsil contracts, and for total hectares of agricultural land cropped by farmers for the individual contract.

3.2 How does basis risk influence crop insurance demand?

To formally assess the impact of basis risk on insurance demand, we estimate how WTP varies with respect to the geographic coverage area of the contract's index. Our measure of spatial coverage—referred to here as "index area"—is the total acreage of cropland (in thousands acres) used for wheat cultivation within the geographic unit underlying the contract (individual, tehsil, or district). Wheat acreage is a relevant metric both for contract design and for farmers' perception of payout reliability. We include contract-type and price support fixed effects, and control for a rich set of farmer-level characteristics selected using a double-selection LASSO procedure. Standard errors are clustered at the farmer level.

Results are presented in Table 1. Column (1) shows a statistically significant and economically meaningful negative relationship between index area and WTP. Specifically, the coefficient implies that a 1,000-acre increase in index area reduces the arcsinh-transformed WTP by 0.0097 units. To interpret magnitudes in levels: the median tehsil area in our sample is approximately 290,000 acres, while the median district covers around 1,300,000 acres. Using our estimated coefficient, this implies that farmers are willing to pay approximately PKR 28 more to remain with the tehsil-level contract rather than switch to the district-level one. This corresponds to roughly 10% of the mean WTP across contracts, suggesting that basis risk meaningfully depresses insurance demand. To better quantify the effect size, we estimate an elasticity of WTP with respect to index area. Using the coefficient -0.0097, for a 10% increase in index area lowers average WTP by roughly 1.2%.

We next explore whether specific farmer characteristics moderate or exacerbate sensitivity to basis risk. Column (2) interacts index area with a binary indicator for whether the farmer reports understanding what insurance is—a proxy for contract comprehension. We find that farmers who report understanding insurance are significantly more sensitive to index area: they are willing to pay PKR 16.5 less per 1,000-acre increase in area compared to those who do not report understanding the product. This result suggests that our average effect in column (1) may understate the true salience of basis risk for attentive or informed farmers.

In Column (3), we interact basis risk with land ownership, finding that farmers with larger landholdings are more averse to basis risk. This is consistent with a higher absolute exposure to uninsured risk due to scale. Column (4) examines interactions with farmers' subjective belief that the insurance will pay out. Farmers with more optimistic or confident beliefs exhibit a weaker response to index area. However, this variable likely captures a conflation of optimism, trust in the provider, and contract comprehension, so we interpret the finding cautiously.

In Column (5), we restrict the sample to farmers for whom we elicited incentive-compatible utility parameters and include these directly in the regression. We find that higher relative risk aversion (RRA) is associated with greater WTP for insurance in the presence of basis risk, while the elasticity of intertemporal substitution (EIS) is negatively associated with demand. The coefficient on time preference is not statistically distinguishable from zero. The positive effect of RRA is noteworthy. It suggests that more risk-averse farmers value insurance more even when coverage is imperfect—a result that contrasts with predictions in Clarke (2016) and Hill et al. (2016), who argue that when premiums are above actuarially fair and basis risk is present, the relationship between risk aversion and demand should be non-monotonic since a risk-neutral agent does not purchase unfair insurance, while a highly risk-averse agent may shy away due to low effective coverage. In our case, the marginal effect of RRA is identified conditional on the level of basis risk, allowing us to isolate preferences from contract features. We further test for non-linearities using risk aversion quartiles and quintiles (Table B3). Across specifications, we find no significant evidence of non-monotonicity, supporting the validity of the linear model over the observed support of risk preferences.

Our findings are robust to alternative outcome definitions. Table B4 shows similar results when using the levels of WTP. Table B5 confirms the pattern on the extensive margin of WTP (i.e., any willingness to pay). We also test the robustness of our spatial index variable by replacing agricultural land area with total land area (Table B6) and by using a measure of basis risk derived from yield correlations within the spatial unit (Table B7). We also estimate a flexible specification using restricted cubic splines for index area to relax the linearity assumption and find no significant evidence of non-linearity (Figure B5). In all cases, the negative effect of basis risk on insurance demand persists.

3.3 How does weather information influence crop insurance demand?

Evidence from the literature suggests that farmers learn from weather events and update their decisions (Gallagher, 2014; Kala, 2017), while a lack of information or inaccurate beliefs can affect their decision-making (Zappalà, 2024). To test whether correcting such misperceptions increases demand, we implement a randomized information intervention. Half of the villages in our study were randomly assigned to receive historical climate data for their sub-district—specifically, average temperature and the number of rainy days during the past ten Rabi seasons. This information was shared with farmers after eliciting their own (subjective) beliefs about past, current, and future weather conditions, but prior to eliciting willingness to pay (WTP) for three alternative index insurance contracts. By introducing the information after beliefs but before bidding, we isolate the causal effect of climate knowledge on insurance demand, separate from preference updating or strategic bias. Appendix Table B2 confirms balance across treatment arms, and Appendix Figure B4 maps treatment assignment spatially.[9]

Table 2 presents our baseline results. Column (1) reports the effect of the weather information treatment on arcsinh-transformed willingness to pay. We find a positive, statistically significant effect: receiving historical weather information increases WTP by 0.23 units. Given a mean arcsinh WTP of 3.51, this implies a 6.6% increase in demand. In column (2), we interact treatment with a binary indicator for whether the farmer overestimated average temperature relative to historical data. We find that the treatment effect is larger for this group, though not statistically significant. Farmers who overestimated recent temperatures may perceive climate risk as greater than it objectively is and could adjust WTP downward once informed. However, in our results, they seem to be more responsive to the treatment. This is consistent with models of confirmation bias or motivated reasoning, where individuals overweight information that

[9]Note that for some villages, we could not obtain the GIS coordinates. Consequently, respondents from those villages are not included on this map.

Table 1: Impact of Basis Risk on the Demand for Crop Insurance

	Willingess to Pay (arcsinh)				
	(1)	(2)	(3)	(4)	(5)
Index Area (in 000'acres)	-0.0097***	-0.0047***	-0.0039***	-0.0061***	-0.0052***
	(0.00054)	(0.00059)	(0.00090)	(0.00062)	(0.00071)
Index Area × Knows Insurance (0/1)		-0.00067**			
		(0.00031)			
Index Area × Land Owned (%)			-0.0012*		
			(0.00069)		
Index Area × Subj. Prob. of Payout				0.0027***	
				(0.00064)	
Time Preference					0.11
					(0.32)
RRA					0.21**
					(0.099)
EIS					-0.015**
					(0.0073)
Outcome mean:	3.7	3.7	3.7	3.7	3.87
Index area mean:	868.92	868.92	868.92	865.79	856.85
N (# of Individuals × Contract)	5310	5310	5310	5283	3462
Individuals	1770	1770	1770	1761	1154
Individual controls		✓	✓	✓	✓
Contract Type FE	✓	✓	✓	✓	✓
Price Support FE	✓	✓	✓	✓	✓
SE	Household	Household	Household	Household	Household
R^2	0.066	0.28	0.28	0.28	0.25

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with Aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * p<0.10, ** p<0.05, *** p<0.01.

aligns with priors and underweight corrective signals (Zappalà, 2023).

A key mechanism by which information may affect insurance demand is by increasing farmers' trust that the index will trigger a payout in adverse states. Columns (3) and (4) show that the information treatment significantly increases the subjective probability that the insurance will pay out, by 4.4 percentage points, which represents a 10.5% increase at the mean (0.42). This provides suggestive evidence that information not only corrects misperceptions but may also increase trust in the product. We find this effect to be smaller among farmers who overestimate temperature, with a statistically significant negative interaction term (column 4), suggesting that farmers who overestimate may disregard corrective information when it conflicts with their prior beliefs.

Finally, we examine the impact of information provision on the difference between WTP and the subjectively expected payout from the insurance contract. Column (5) shows that the weather information treatment reduces this difference by PKR 2213, a statistically significant drop equivalent to 23.3% of the mean. This suggests that correcting beliefs realigns WTP with perceived value, mitigating behavioral frictions that create a wedge between willingness to pay and the subjective probability of payout. We find that this effect is smaller for those whose priors overestimate historical temperatures (column 6). The treatment reduces the difference by PKR 4444 among those with accurate priors but only by PKR 3402 among farmers who overestimate historical temperatures. This finding is consistent with previous heterogeneous results where belief updating is asymmetric and individuals whose priors overestimate temperatures may discount new evidence more heavily, especially if it suggests less frequent payouts than they originally believed.

Table 2: Impact of Weather information on the Demand for Crop Insurance

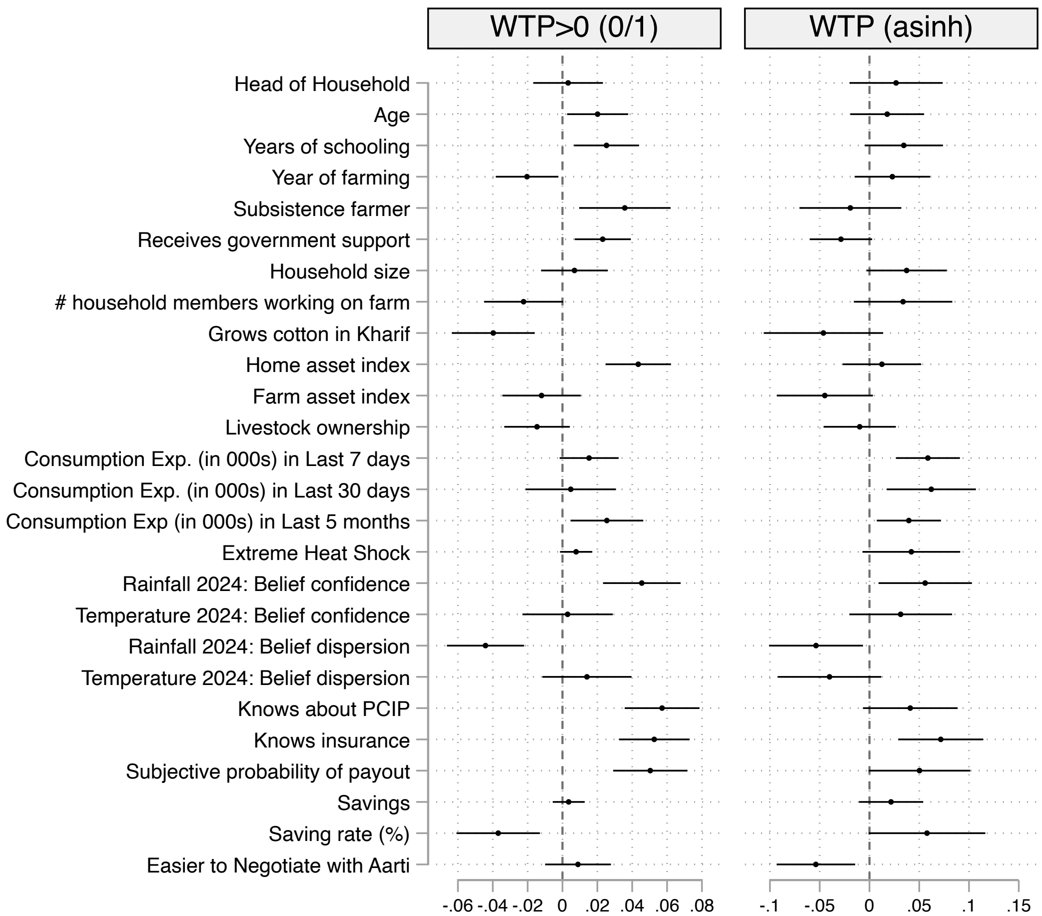
	Willingess to Pay (arcsinh)		Subjective Probability of Payout		Willingess to Pay - Expected Payout	
	(1)	(2)	(3)	(4)	(5)	(6)
Weather Information	0.23*	0.040	0.044***	0.077***	-2213.1***	-4444.5**
	(0.13)	(0.19)	(0.013)	(0.022)	(833.4)	(1793.6)
Overestimating Prior Beliefs		-0.061		0.048***		-2527.2
		(0.16)		(0.017)		(1544.3)
Weather Information × Overestimating Prior Beliefs		0.31		-0.053**		3569.8*
		(0.21)		(0.024)		(1870.5)
Dep. Var - Mean:	3.51	3.51	0.42	0.42	-9507.67	-9507.67
R^2	0.42	0.42	0.50	0.50	0.13	0.14
# of Individual-Contract Pairs	5334	5334	5307	5307	5307	5307
Individuals	1778	1778	1769	1769	1769	1769
Controls	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Contract FE	✓	✓	✓	✓	✓	✓
Price FE	✓	✓	✓	✓	✓	✓
SE	Village	Village	Village	Village	Village	Village

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with Aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * p<0.10, ** p<0.05, *** p<0.01.

3.4 What factors influence the demand for crop insurance?

We conclude our analysis on the determinants of crop insurance demand by examining farmer-level factors that influence the demand for crop insurance (both in the extensive and intensive margins). For the extensive margin, we use an indicator variable that takes value of one if the individual is willing to pay a strictly positive amount for an insurance contract, and 0 if they wish to obtain insurance but are not inclined to pay any positive amount for it (i.e., WTP is zero). To capture the intensive margin, we use the arcsinh-transformed willingness to pay. We account for price support and contract fixed effects and use standardized farmer-level (contract invariant) characteristics. We present results in Figure 3 and summarize the findings below.

Figure 3: Predictors of crop insurance demand (extensive and intensive margin)



Notes: Figure shows coefficient estimates from separate regressions of each standardized independent variable on a positive willingness to pay for crop insurance (WTP>0 (0/1)) and on the intensive margin of crop insurance demand using the arcsinh of stated WTP, respectively. Horizontal lines represent 95% confidence intervals. Standard errors are clustered at the farmer-level. Village, price-support, and contract fixed effects are included in all specifications.

Household Characteristics. On the extensive margin, we find that older, more educated farmers, those who rely significantly on their production for household consumption (subsistence farmers), and those who have previously received government support are more likely to pay for crop insurance. Conversely, those with more years of farming experience, more household members working on the farm, those growing cotton (a cash crop), and those involved in livestock farming are the least likely to pay for crop insurance. When it comes to purchasing insurance, we do not observe any of these factors influencing the intensive margin. Additionally, we do not find any effect of household size on either the extensive or intensive margin.

Wealth and Income. We find that home assets (a proxy for wealth) have a positive and statistically significant relationship with the uptake of crop insurance. In contrast, farm assets do not affect the extensive margin. However, when conditioned on the willingness to pay for insurance (intensive margin), we observe opposing effects for home and farm assets. Specifically, those with more home assets (likely less productive assets) are inclined to pay more for crop insurance (though this is not statistically significant). Conversely, individuals with more farm assets (likely more productive) tend to pay less for crop insurance. Using consumption expenditure as a proxy for income, we find that those with greater consumption (over 7 days, 30 days, and 5 months) are not only more likely to take up crop insurance but are also willing to pay more as their expenditure increases. This suggests a positive relationship between income and the willingness to insure against negative shocks.

Climate Experience and Beliefs. We find evidence that exposure to extreme heat shock leads to an increase in the uptake of crop insurance, suggesting that experiencing an adverse yield loss event positively impacts uptake, in line with existing evidence on learning (e.g., Gallagher (2014)). Furthermore, farmers' confidence in weather and their understanding of the relationship between weather and yields also influence their demand for crop insurance. A more confident farmer may have a better grasp of the risks and thus be more willing to invest in crop insurance if they believe that weather affects their yields. We find evidence that farmers are not only willing to pay for crop insurance, but they are also inclined to pay more if they are more confident in their assessment of rainy days (last year, this year, and ten years from now), although this is not the case for temperature.

Insurance Understanding and Trust. Several studies highlight the importance of financial literacy and understanding in the uptake of insurance (Cai et al., 2020; Casaburi and Willis, 2018). We also find supporting evidence: farmers who are knowledgeable about insurance (in general) and those who understand the insurance scheme are more likely to pay for crop insurance. Moreover, among those willing to pay, they are inclined to pay more.

Additionally, trust has been identified as a major constraint in the demand for crop insurance. Farmers, who are often cash-constrained, must pay the premium upfront and rely on the insurance company to compensate them in the event of a negative shock, such as yield loss. We asked farmers how likely they believe the insurance contract will pay out, using this as a proxy for trust. Our findings indicate that those who have greater confidence in receiving a payment are more inclined to purchase crop insurance (extensive margin) and are also willing to pay more (intensive margin).

Existing Insurance Mechanisms: Savings, Loans and Informal Networks. Alternatives to formal crop insurance, such as savings (self-insurance) or informal networks, may reduce the need for formal crop insurance. We observe a negative and statistically significant effect of savings on insurance uptake. However, conditional on willingness to pay, we note a positive and statistically significant impact regarding how much farmers are willing to pay. This indicates that self-insurance can diminish the necessity for formal insurance, but those who are willing to pay are likely to contribute more, as their savings provide them with the means to do so.

Farmers can depend on their existing network to safeguard against negative shocks. We do not find evidence that borrowing from others affects their decision to pay for crop insurance. In Punjab's agricultural landscape, Aarti plays a central role in the supply chain. Aarti often provides farmers with inputs on credit in exchange for cash or harvest at the season's end, and may also sell farmers' harvest on their behalf for a commission. Additionally, Aarti can offer farmers informal insurance by relaxing credit contracts when the farmers (or community) experience negative shocks, potentially crowding out demand for crop insurance. We asked farmers if they could renegotiate with Aarti during a negative shock. We find that the ease of negotiation with Aarti does not influence the extensive margin decision to pay for insurance; however, we do find evidence that farmers with more accommodating Aartis (i.e., those willing to renegotiate) are less inclined to pay for crop insurance. This suggests that while farmers value formal crop insurance, they are willing to rely on their informal insurance networks as much as possible.

4 Model of crop insurance demand

Our set of empirical results from the survey establish that both contract features in the form of basis risk and behavioral factors such as misinformed beliefs and individual preferences significantly shape farmers' willingness to pay for crop insurance. We now develop a structural model to quantify their joint contribution to insurance demand. This framework allows us to take stock of our reduced-form findings and embed them in a unified model of farmer decision-making under uncertainty. Our goal is to recover deep parameters governing preferences and beliefs, simulate counterfactual demand under varying frictions, and assess the welfare implications of expanding access to climate adaptation tools such as index insurance.

4.1 Setup

We model the intertemporal insurance decision of farmer i located in tehsil T within district D using Epstein–Zin preferences, which allow for a separation between relative risk aversion and the elasticity of intertemporal substitution (a significant departure from earlier works in insurance theory (e.g., Clarke, 2016). Farmer utility over consumption streams $(c_{i,t}, c_{i,t+1})$ under insurance contract $j \in I, T, D, \emptyset$ — where I, T, and D correspond to individual-, tehsil-, and district-level contracts, and $\emptyset$ denotes no insurance — is given by:

$$U_i = \left[(1-\beta)(c^j_{i,t})^\rho + \beta\left(\mathbb{E}_i(c^j_{i,t+1})^\alpha\right)^{\frac{\rho}{\alpha}}\right]^{\frac{1}{\rho}}, \tag{1}$$

where β is the time discount factor, $1/(1-\rho)$ is the elasticity of intertemporal substitution (EIS), and $(1-\alpha)$ is the coefficient of relative risk aversion (RRA). The expectation operator $\mathbb{E}_i$ is taken with respect to farmer i's subjective beliefs about the realization of future states of the world.

At the start of the agricultural season, farmers choose whether and which contract j to purchase at premium price p_j (with $p_\emptyset = 0$ for the uninsured case). At the end of the season, weather is realized, which determines both income and the payout (if any) from the chosen insurance contract.

We assume farmers face a simple two-period budget constraint (ignoring savings or credit access and assuming only full coverage insurance, akin to the PCIP)

$$c^j_{i,t} + p_j = y_{i,t} \tag{2}$$

$$c^j_{i,t+1} = \pi^j[\delta y_{i,t+1} + P] \tag{3}$$

where $y_{i,t}$ is income at time t; $\delta \in [0, 1]$ is the proportion of income preserved after a shock; P is the payout (equal across contracts); and π^j captures the probability that the farmer in one of the four states of the world under contract j, where the states of the world are: (Loss, Trigger), (Loss, No Trigger), (No Loss, Trigger), and (No Loss, No Trigger). Note that when the probability of case two is strictly positive, i.e., there is an individual loss but no trigger, this case is often referred to as *basis risk*. In case of the trigger, farmers receive the insurance payout P (same across insurance contracts).

4.2 Insurance contract features

All three insurance contracts pay the exact amount P, but they differ in terms of the criterion based on when those payouts are triggered. In particular, they depend upon the average yield at a given spatial unit, which we formalize below. The government conducts cross-cut experiments to recover average yield at a given spatial unit (subdistrict, district, etc.), and the way they do this is by using a pre-set size of the farmland, and randomly selecting plots across the spatial unit to compute average yield in those plots. Given that the denominator is held constant, the mean of the average yields within a given spatial unit is equivalent to dividing the total production on these plots in a spatial unit by the total area.

Each insurance contract j pays out after the state of the world is realized (index triggered or not) and it is based on an area-index yield computed over a spatial unit j. Let $\mathcal{I}_j$ be the set of farmers in spatial unit j, with $1 = \mathcal{I}_I < \mathcal{I}_T < \mathcal{I}_D$. Let $\bar{y}_{j,t+1}$ be the average yield in spatial unit j at the end of the season (where $\bar{y}_I = y_i$ in the case of individual yield).

A claim is triggered if the index yield falls below 80% of historical ten-year average $\bar{y}_j^{\text{avg}}$, where j is district for district-level insurance and tehsil for both teshil- and individual-level insurance, such that the payout structure P is

$$P = \begin{cases} L & \text{if } \bar{y}_j^s < 0.8 \cdot \bar{y}_j^{\text{avg}} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where L is 30,000 PKR per acre.

4.3 Basis risk

The difference between a farmer's own realized yield y_i^s and the index yield $\bar{y}_j^s$ in a given state s is the basis error:

$$\varepsilon_{ij}^s = y_i^s - \bar{y}_j^s \tag{5}$$

and $P_0^s = 0$ in any state of the world, so, no insurance, no payout. Note that the probability of the index being triggered is contract-specific and the index is not perfectly correlated with the loss except in the case of an individual-level index. This is what generates basis risk, which is the variance of basis error, i.e., the risk that an insured individual faces:

$$Var(\varepsilon_{ij}^s) = Var(y_i^s - \bar{y}_j^s) \tag{6}$$

we now derive this as a function of spatial unit j size. We assume the following that each farmer $i \in \mathcal{I}_j$ in spatial unit j cultivates a fixed amount of land ℓ. This simply means that no new arable land can be created within spatial unit j. So total land cultivated in j is $L_j = \mathcal{I}_j \cdot \ell$. That land cultivated is fixed in period 0 and 1 assumes farmers commit to before the beginning of the growing season. The assumption that the all farmers cultivate a fixed amount of land means that no farmer can influence the average yield alone. We define yield for farmer i in state s as $y_i^s = \mu_s + \eta_i^s$, where μ_s is a common (systemic) component that is state-specific but farmer-invariant, and η_i^s, which is an idiosyncratic component, such that:

$$\mathbb{E}[\eta_i^s] = 0, \quad Var(\eta_i^s) = \sigma^2, \quad Cov(\eta_i^s, \eta_k^s) = \rho\sigma^2 \text{ for } i \neq k \tag{7}$$

The average yield in spatial unit j, which we need for the index, is

$$\bar{y}_j^s = \frac{1}{\mathcal{I}_j} \sum_{k \in \mathcal{I}_j} y_k^s = \mu_s + \frac{1}{\mathcal{I}_j} \sum_{k \in \mathcal{I}_j} \eta_k^s = \mu_s + \bar{\eta}_j^s \tag{8}$$

Then, we can rewrite the basis error for farmer i as

$$\varepsilon_{ij}^s = y_i^s - \bar{y}_j^s = \eta_i^s - \bar{\eta}_j^s \tag{9}$$

and so basis risk as

$$Var(y_i^s - \bar{y}_j^s) = Var(\eta_i^s - \bar{\eta}_j^s), \tag{10}$$

which gives us (full derivation in Appendix Section A)

$$Var(\eta_i^s - \bar{\eta}_j^s) = Var(\eta_i^s) + Var(\bar{\eta}_j^s) - 2 \cdot Cov(\eta_i^s, \bar{\eta}_j^s) \quad = \sigma^2 \left(1 + \rho - \frac{1 + \rho + 2(\mathcal{I}_j - 1)\rho}{\mathcal{I}_j}\right) \tag{11}$$

if we replace $\mathcal{I}_j = \frac{L_j}{\ell}$, and rearrange, we obtain

$$Var(y_i^s - \bar{y}_j^s) = Var(\eta_i^s - \bar{\eta}_j^s) \quad = \sigma^2 \left(1 - \rho - \frac{\ell(1 - \rho)}{L_j}\right) \tag{12}$$

First, we note that if $\mathcal{I}_j = 1$, then $\ell = L_j$, which brings us to a case where basis risk is 0. Second, basis risk is increasing in spatial unit size L_j, and at the limit, when it is equal to infinity, we obtain maximum basis risk $(\sigma^2(1-\rho))$. Third, higher correlation in the idiosyncratic component across farmers ρ reduces basis risk, ceteris paribus.

4.4 Willingness to Pay for crop insurance

The maximum price $\tilde{D}_{ij}(\alpha, \beta, \rho, Var(\varepsilon^s_{ij}))$ that the farmer i is willing to pay for insurance contract j depends on its utility parameters (α, β, ρ), its subjective beliefs π^s, the basis risk of the insurance contract $Var(\varepsilon^s_{ij})$, and the expected payout $q_{ij}L$. We define this as the farmer's *theoretical willingness to pay* for contract j that equalizes the utility from being insured and from remaining uninsured:

$$U_{ij}(\tilde{D}_{ij}) = U_{i0} \tag{13}$$

Using Epstein-Zin preferences, we obtain

$$\left[(1-\beta)(y_i - \tilde{D}_{ij})^\rho + \beta\left(\mathbb{E}_i\left[(y^s_i + P^s_j)^\alpha\right]^{\frac{\rho}{\alpha}}\right)\right]^{\frac{1}{\rho}} = \left[(1-\beta)y^\rho_i + \beta\left(\mathbb{E}_i\left[(y^s_i\right]^{\frac{\rho}{\alpha}}\right)\right]^{\frac{1}{\rho}} \tag{14}$$

This implicitly defines the theoretical willingness to pay $\tilde{D}ij(\alpha, \beta, \rho, \pi^s_i, \text{Var}(\varepsilon ij^s))$, which we use to simulate counterfactuals and estimate welfare losses from frictions.

5 Estimating a structural model for crop insurance

5.1 Calibration

This section is in progress and incomplete. In this section, we outline the next steps in our structural quantification exercise, which leverages the empirical findings from our field experiment. Our objective is to estimate a model of crop insurance demand that recovers individual preferences, accounts for subjective beliefs over climate, and evaluates the welfare effects of adaptation through crop insurance under behavioral frictions and basis risk.

We begin by estimating utility parameters using incentivized multiple price list tasks administered in the field. Following Brown and Kim (2014), we adopt an Epstein-Zin recursive utility function of the form:

$$U = \left[(1-\beta)(c_t)^\rho + \beta\left(c^\alpha_{t+1}\right)^{\frac{\rho}{\alpha}}\right]^{\frac{1}{\rho}}, \tag{15}$$

where ρ governs the elasticity of intertemporal substitution, α captures risk aversion, and β is the time discount factor. In our static setting, we recover ρ and β from two complementary games.

We elicit intertemporal preferences by asking respondents how much more they would need to receive to wait one week for a payment. Denoting the immediate reward as 80 PKR and the delayed reward as x, the switch point implies bounds on the β–ρ relationship:

$$(1-\beta)^{\frac{1}{\rho}}(80) > \beta^{\frac{1}{\rho}}(x) \quad \Rightarrow \quad \frac{\beta}{1-\beta} < \left(\frac{80}{x}\right)^{\rho},\ (1-\beta)^{\frac{1}{\rho}}(80) \quad < \beta^{\frac{1}{\rho}}(x+10) \quad \Rightarrow \quad \frac{\beta}{1-\beta} > \left(\frac{80}{x+10}\right)^{\rho}. \tag{16}$$

These inequalities jointly restrict the feasible set of values for (β, ρ). We also elicit risk preferences by offering farmers a series of lotteries over the delayed amount x versus a certain payment. From the switch point in this risk task, we infer the following bounds on ρ:

$$(1-\beta)^{\frac{1}{\rho}}(80) > \Big[(1-\beta)((z-5)(1-\beta)^{\frac{1}{\rho}}(80) \qquad\qquad < [(1-\beta)(z \tag{17}$$

We then estimate (ρ, β) using maximum likelihood, pooling information across switch points. Risk aversion α is recovered from a separate lottery game using standard CRRA estimation.

In the next stage of the model, we incorporate two key inputs:

- Subjective climate beliefs, elicited through a bean allocation exercise over five temperature and precipitation states, which we map into subjective probability distributions.
- The systemic yield component, estimated from household survey responses and calibrated using historical climate-yield covariance at the tehsil level.

Together, these components allow us to simulate expected utility from each insurance contract under each farmer's preferences and beliefs, and to estimate demand structurally. Counterfactual exercises will evaluate how contract design, basis risk, and corrected beliefs affect welfare.

5.2 Counterfactuals

With estimated utility parameters and subjective beliefs in hand, we use the structural model to simulate willingness to pay (WTP) under a series of counterfactual scenarios designed to isolate the role of behavioral frictions and contract features. Specifically, we consider the following three counterfactuals:

1. **No Basis Risk:** We eliminate basis risk by setting the index yield equal to the farmer's realized yield in each state, i.e., $\bar{y}_j^s = y_i^s$.
2. **Correct Beliefs:** We replace farmers' subjective probability distributions π_i^s with objective empirical climate distributions derived from historical data
3. **Rational Preferences:** We replace estimated utility parameters $(\alpha_i, \rho_i, \beta_i)$ with benchmark values consistent with fully rational, expected utility maximization—e.g., $\alpha = \rho = 0.5$, $\beta = 0.95$

These scenarios allow us to generate counterfactual WTPs for each farmer-contract pair:

$$\hat{p}_{ij}^{\mathsf{CF}} = \mathsf{WTP}ij(\text{no basis risk, correct beliefs, rational preferences}), \tag{18}$$

and to simulate counterfactual demand curves by varying one friction at a time while holding others constant. This decomposition allows us to derive a welfare-relevant ranking of constraints to insurance adoption.

5.3 Welfare and Insurance Value

To assess the welfare implications of insurance uptake, we define the *value of insurance* for farmer i from purchasing contract j at price p_j as:

$$V_{ij} = U_{ij}(p_j) - U_{i0} \tag{19}$$

where $U_{ij}(p_j)$ is the expected utility under the insurance contract and U_{i0} is the utility without insurance.

We then define the *welfare loss due to frictions* as the difference between the value of insurance under the counterfactual scenario (free from frictions) and the observed scenario:

$$\Delta V_{ij} = V_{ij}^{\mathsf{CF}} - V_{ij}^{\mathsf{Observed}}. \tag{20}$$

This framework allows us to decompose welfare losses into components attributable to (i) basis risk, (ii) biased climate beliefs, and (iii) non-EU or non-rational preferences—providing quantitative guidance for contract design and behavioral interventions to improve insurance uptake.

6 Conclusion

Small agricultural households face significant climate risks and are among the least prepared to cope with the consequences, let alone invest in adaptive technologies, which can often be risky or costly. Current levels of adaptation in the sector are inadequate for food security (Hultgren et al., 2022), and innovative solutions are essential to address the challenges facing much of the developing world, particularly its fragile agricultural sector made up of small-scale farmers.

We conduct a survey of over 2,000 small-scale farm households from more than a hundred villages in Punjab, Pakistan, to document how farmers are responding to extreme heat shocks, their demand for crop insurance, and the factors influencing this demand, including the characteristics of the insurance contract and weather information.

We investigate farmers' willingness to pay (WTP) for insurance contracts that vary based on the index they cover, which serves as a proxy for basis risk—a mismatch between individual and index losses. Over 90% of farmers are interested in crop insurance; however, only half of the sample is willing to pay for it, while 40% prefer it for free. Several household characteristics correlate with the willingness to pay at both extensive and intensive margins, including age, education, years of farming, assets, income, confidence in predicting weather, understanding of insurance, trust in payouts, and avenues for coping with shocks through self-insurance or informal networks. We also found a negative and statistically significant relationship between the demand for crop insurance and the index area, providing evidence that basis risk (proxied by the area index) is a key constraint on crop insurance demand. Lastly, we find that the provision of weather information may not necessarily enhance the demand for area-yield based insurance, but it can signal to farmers about insurance payouts and thus improve trust, leading to greater uptake of crop insurance.

Our results suggest that small-scale farmers in developing countries may have limited resources to manage interconnected community-wide shocks. However, there is considerable demand for crop insurance, particularly those that address local community-wide shocks. Additionally, efforts to build trust and enhance understanding of insurance schemes can significantly influence the household risk management strategies currently in place.

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Online Supplementary Material "Demand for Crop Insurance: Evidence from Pakistan"

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A Derivation of basis risk

We compute basis risk using the properties of the mean of correlated variables

$$
\begin{aligned}
Var(\eta_i^s - \bar{\eta}_j^s) &= Var(\eta_i^s) + Var(\bar{\eta}_j^s) - 2 \cdot Cov(\eta_i^s, \bar{\eta}_j^s) \\
&= \sigma^2 + \frac{1}{I_j^2}\left(I_j\sigma^2 + I_j(I_j-1)\rho\sigma^2\right] - 2 \cdot \frac{1}{I_j}\left(\sigma^2 + (I_j-1)\rho\sigma^2\right] \\
&= \sigma^2 + \frac{\sigma^2}{I_j^2}\left(I_j + (I_j^2 - I_j)\rho\right] - \frac{2\sigma^2}{I_j}\left(1 + (I_j-1)\rho\right] \\
&= \sigma^2 + \sigma^2\left(\frac{1}{I_j} + \rho - \frac{\rho}{I_j}\right] - \frac{2\sigma^2}{I_j}\left(1 + (I_j-1)\rho\right] \\
&= \sigma^2\left(1 + \frac{1}{I_j} + \rho - \frac{\rho}{I_j} - \frac{2}{I_j} - \frac{2(I_j-1)\rho}{I_j}\right] \\
&= \sigma^2\left(1 + \rho - \frac{1+\rho+2(\mathcal{I}_j-1)\rho}{\mathcal{I}_j}\right)
\end{aligned}
\tag{A.1}
$$

where to obtain the variance of an average of correlated variables we use the formula

$$
\begin{aligned}
Var(\bar{\eta}_j^s) &= \frac{1}{I_j^2}\left[I_j \cdot Var(\eta_k^s) + I_j(I_j-1) \cdot Cov(\eta_k^s, \eta_{k'}^s)\right] \\
&= \frac{1}{I_j^2}\left[I_j\sigma^2 + I_j(I_j-1)\rho\sigma^2\right] \\
&= \frac{\sigma^2}{I_j^2}\left[I_j + (I_j^2 - I_j)\rho\right]
\end{aligned}
\tag{A.2}
$$

and for the covariance between the individual shock and the average, we use

$$
\begin{aligned}
Cov(\eta_i^s, \bar{\eta}_j^s) &= Cov\left(\eta_i^s, \frac{1}{I_j}\sum_k \eta_k^s\right) \\
&= \frac{1}{I_j}\sum_k Cov(\eta_i^s, \eta_k^s) \\
&= \frac{1}{I_j}\left[Var(\eta_i^s) + (I_j - 1)\cdot Cov(\eta_i^s, \eta_k^s)\right] \\
&= \frac{1}{I_j}\left[\sigma^2 + (I_j - 1)\rho\sigma^2\right] \\
&= \frac{\sigma^2}{I_j}\left[1 + (I_j - 1)\rho\right]
\end{aligned}
\tag{A.3}
$$

B Figures and Tables

Figure B1: Experimental Design and Timeline

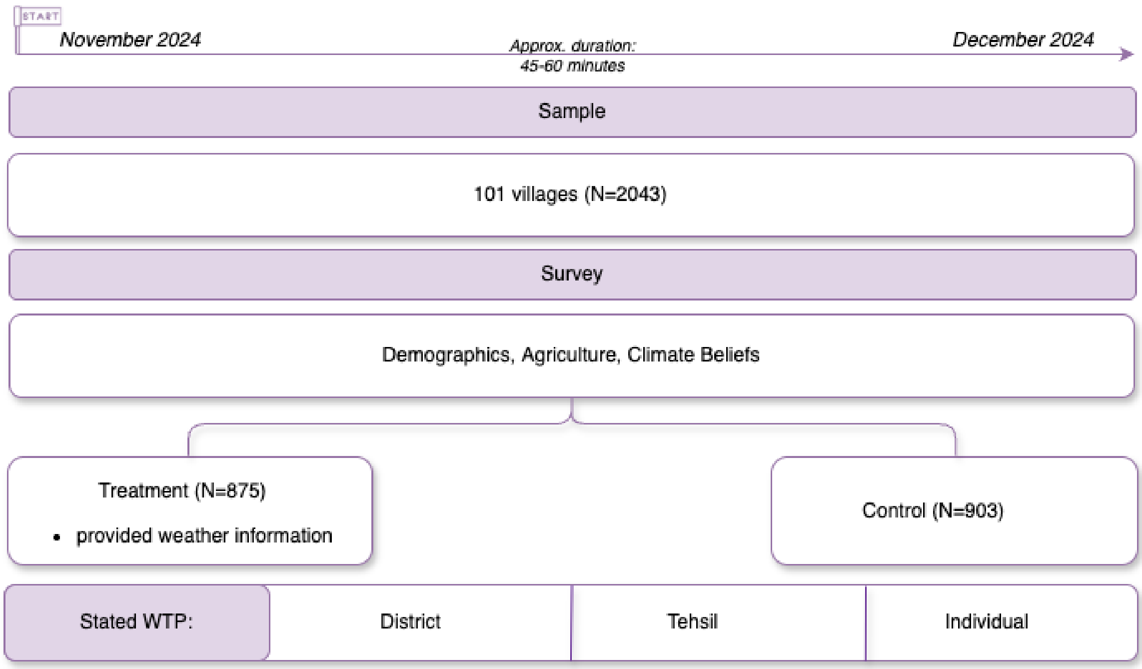
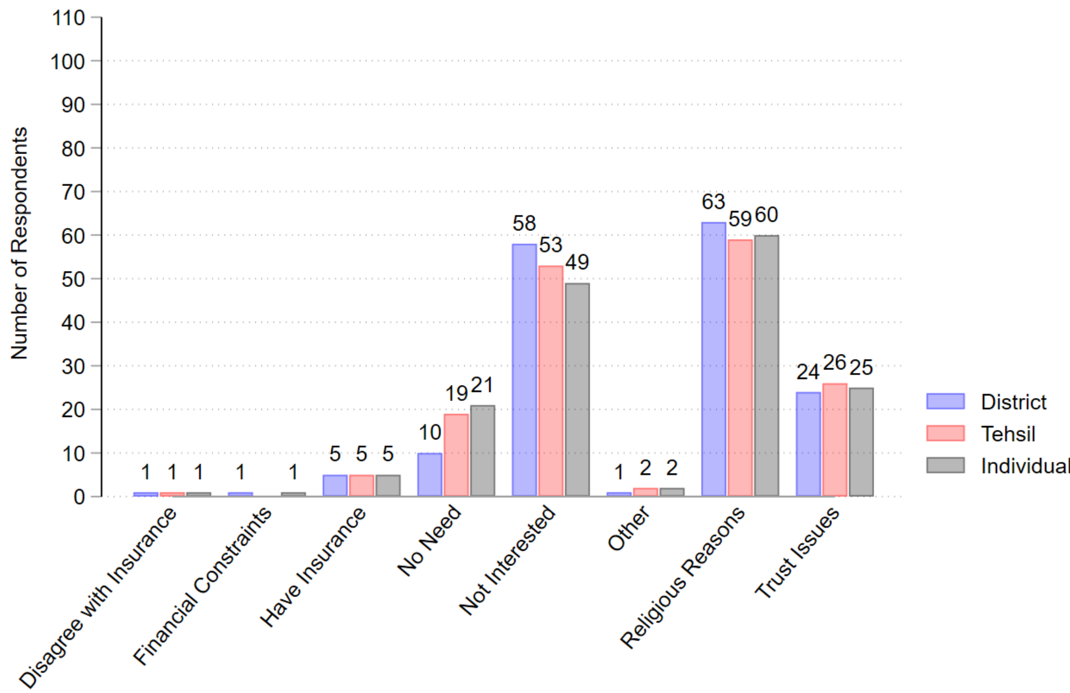


Table B1: Summary Statistics

	N	Mean	SD	Median	Min	Max
Age (Max =80)*	2043	40.45	10.91	39.00	18.00	80.00
Married (1/0)	2043	0.92	0.27	1.00	0.00	1.00
Years of Schooling (Max =16)	2043	6.71	4.52	8.00	0.00	16.00
Years of Farming (Max =65)*	2043	17.20	9.61	15.00	2.00	65.00
Household Size (Max =21)*	2043	6.51	2.54	6.00	1.00	21.00
# of Household Members Working on Farm	2043	1.92	1.18	2.00	0.00	7.00
Prop. of Household Members Working on Farm	2043	0.30	0.16	0.29	0.00	1.00
Non-agri Income (1/0)	2043	0.18	0.39	0.00	0.00	1.00
Consumption Expenditure (in 000s) in Last 7 days	2043	10.33	11.34	8.00	0.00	150.00
Consumption Expenditure (in 000s) in Last 30 days	2043	49.11	94.14	35.00	0.00	2500.00
Consumption Expenditure (in 000s) in Last 5 months	2043	246.87	346.84	185.00	0.00	7000.00
Home Asset Index (Max =33)	2043	9.36	5.36	8.00	0.00	33.00
Farm Asset Index (Max =9)	2043	1.84	2.34	1.00	0.00	9.00
Number of Farm Plots Used (Max =55)*	2043	5.14	4.95	4.00	0.00	55.00
Number of Farm Plots Owned (Max =55)	2043	4.74	4.72	3.00	0.00	55.00
Kharif 24: Cotton (1/0)	2043	0.39	0.49	0.00	0.00	1.00
Acres Cultivated (avg. across all season)*	2043	8.09	19.73	5.00	0.50	636.00
Acres Fallow (avg. across all season)	2043	0.39	1.50	0.00	0.00	33.33
# of Farmers who Grew Any Crop in Rabi 2024	1984	1.00	0.00	1.00	1.00	1.00
Rabi 24: Wheat (1/0)	2043	0.97	0.18	1.00	0.00	1.00
# of Farmers Who Grew Wheat in Rabi 2024	1978	1.00	0.00	1.00	1.00	1.00
Rabi 24: Average Yield (Primary, kg/acre, in 000s)	1978	3.34	7.80	1.80	0.00	148.00
Rabi 24: Primary Crop Revenue (in 000000s)	1978	198.17	5812.52	0.38	0.00	206500.00
Rabi 24: Primary Crop Cost (in 000s)	1978	252.15	341.23	158.75	16.20	4996.00
Rabi 24: HH Consumption (kg, in 000s)*	1978	1.50	9.86	0.80	0.00	400.00
Rabi 24: Harvest Sale (kg, in 000s)*	1978	30.01	481.01	4.80	0.00	14000.00
Rabi 25: Wheat (1/0)	2043	1.00	0.00	1.00	1.00	1.00
Irrigation Canal (1/0)	2043	0.54	0.50	1.00	0.00	1.00
Irrigation: River or Lakes (1/0)	2043	0.06	0.23	0.00	0.00	1.00
Irrigation: Tubewell (1/0)	2043	0.86	0.34	1.00	0.00	1.00
Irrigation: Rain-fed (1/0)	2043	0.48	0.50	0.00	0.00	1.00
Owned Any Livestock (1/0)	2043	0.76	0.42	1.00	0.00	1.00
Livestock Profits (in 000s)	2043	25.88	168.10	0.00	-2775.00	1520.00
Took Loan (1/0)	2043	0.17	0.38	0.00	0.00	1.00
Government Support (1/0)	2043	0.11	0.31	0.00	0.00	1.00
Saving (in 000s)	2043	182.58	459.06	50.00	-0.10	11000.00
Easier to Negotiate with Aarti (1/0)	2043	0.22	0.42	0.00	0.00	1.00
Know about Insurance (1/0)	2043	0.74	0.44	1.00	0.00	1.00
Survey Week (relative to planting time)	2043	4.68	5.82	4.00	-24.00	20.00
Extreme Heat Shock (Rabi 2022-23)	2043	116.81	137.57	77.04	77.04	770.41
Extreme Heat Shock (Rabi 2023-24)	2043	104.45	123.01	68.89	68.89	688.90
# of villages	101					

Note: This table presents summary statistics for farmers who grew wheat as a primary crop in Rabi 2025.

Figure B2: Reason to Not Insure



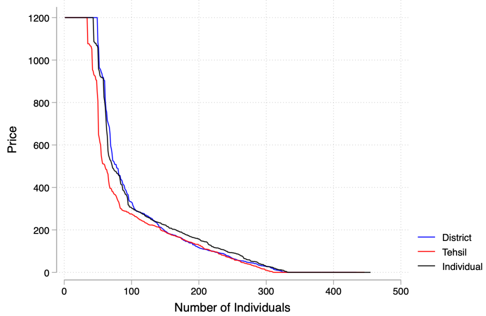
Note: The figure shows reasons reported as barriers to insurance uptake by contract type.

Table B2: Balance Table

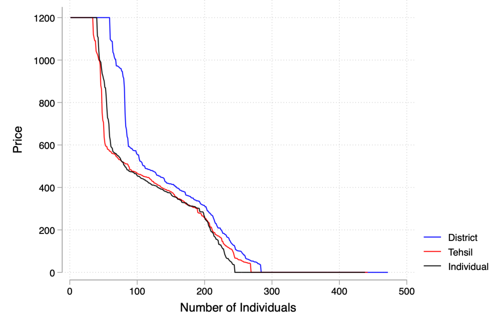
	Main Sample==1			Main Sample==0			
	N	Mean	SD	N	Mean	SD	P-value
Age (Max =80)*	903	40.38	10.82	875	39.46	10.56	0.43
Years of Schooling (Max =16)	903	6.49	4.36	875	6.88	4.65	0.37
Years of Farming (Max =65)*	903	16.97	9.45	875	16.61	9.21	0.75
Household Size (Max =21)*	903	6.55	2.62	875	6.45	2.26	0.70
Subsistence*	903	0.20	0.18	875	0.16	0.16	0.18
Owned Any Livestock (1/0)	903	0.75	0.43	875	0.79	0.41	0.37
# of Household Members Working on Farm	903	1.98	1.19	875	1.92	1.18	0.71
Home Asset Index (Max =33)	903	8.92	5.10	875	9.43	5.61	0.41
Farm Asset Index (Max =9)	903	1.82	2.43	875	1.99	2.34	0.63
Consumption Expenditure (in 000s) in Last 7 days	903	9.30	9.51	875	10.20	11.27	0.31
Consumption Expenditure (in 000s) in Last 30 days	903	46.53	58.52	875	47.69	95.86	0.85
Consumption Expenditure (in 000s) in Last 5 months	903	234.99	225.12	875	249.43	391.27	0.61
Kharif 24: Cotton (1/0)	903	0.44	0.50	875	0.37	0.48	0.33
Know about Insurance (1/0)	903	0.69	0.46	875	0.75	0.43	0.24
Fully Understand Insurance Scheme (1/0)	903	0.82	0.39	875	0.85	0.36	0.61
Saving Rate (in percentage)*	903	13.12	15.40	875	15.18	15.67	0.35
Took Loan (1/0)	903	0.17	0.38	875	0.19	0.39	0.73
Government Support (1/0)	903	0.11	0.31	875	0.12	0.33	0.61
Easier to Negotiate with Aarti (1/0)	903	0.25	0.43	875	0.22	0.41	0.40
Survey Week (relative to planting time)	903	5.69	4.64	875	5.32	3.89	0.46
Expected Probability of Payout of the Contract (District)	903	0.40	0.22	866	0.44	0.23	0.28
Expected Probability of Payout of the Contract (Tehsil)	903	0.40	0.22	866	0.44	0.23	0.23
Expected Probability of Payout of the Contract (Individual)	903	0.39	0.23	866	0.43	0.22	0.16
Ideal Rain: Measure of confidence	903	0.69	0.32	875	0.67	0.32	0.65
Rain 23: Measure of Confidence	903	0.70	0.32	875	0.67	0.32	0.48
Rain 24: Measure of Confidence	903	0.70	0.32	875	0.66	0.32	0.33
Rain 34: Measure of Confidence	903	0.54	0.35	875	0.54	0.34	0.97
Ideal Temp: Measure of confidence	903	0.58	0.32	875	0.55	0.30	0.62
Temp 23: Measure of Confidence	903	0.54	0.31	875	0.53	0.30	0.80
Temp 24: Measure of Confidence	903	0.55	0.32	875	0.53	0.30	0.74
Temp 34: Measure of Confidence	903	0.49	0.33	875	0.48	0.30	0.80
Risk (Switch)	903	3.90	3.06	875	4.45	3.03	0.03
Irrigation: Canal	903	0.58	0.49	875	0.52	0.50	0.36
Irrigation: River or Lakes	903	0.04	0.20	875	0.09	0.28	0.11
Irrigation: Tubewell	903	0.88	0.32	875	0.85	0.35	0.60
Irrigation: Rain-fed	903	0.50	0.50	875	0.52	0.50	0.80

Notes: This table presents the number of observations, means, and standard deviations for key characteristics of our sample in the treatment and control groups. Columns (1)–(3) report the number of observations, mean, and standard deviation for the control group, while columns (4)–(6) report the same for the treatment group. Column (7) reports p-values from regressions testing whether the mean differences between the treatment and control groups are statistically significant. Standard errors are clustered at the village level. The results are restricted to farmers who are part of the main sample.

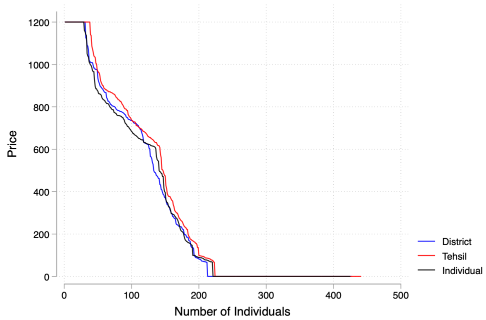
Figure B3: Inverse demand curve for crop insurance by contract type and price support



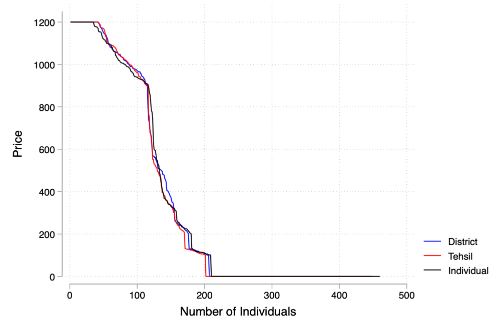
(a) Price Support: $\mathcal{U}(0, 300]$



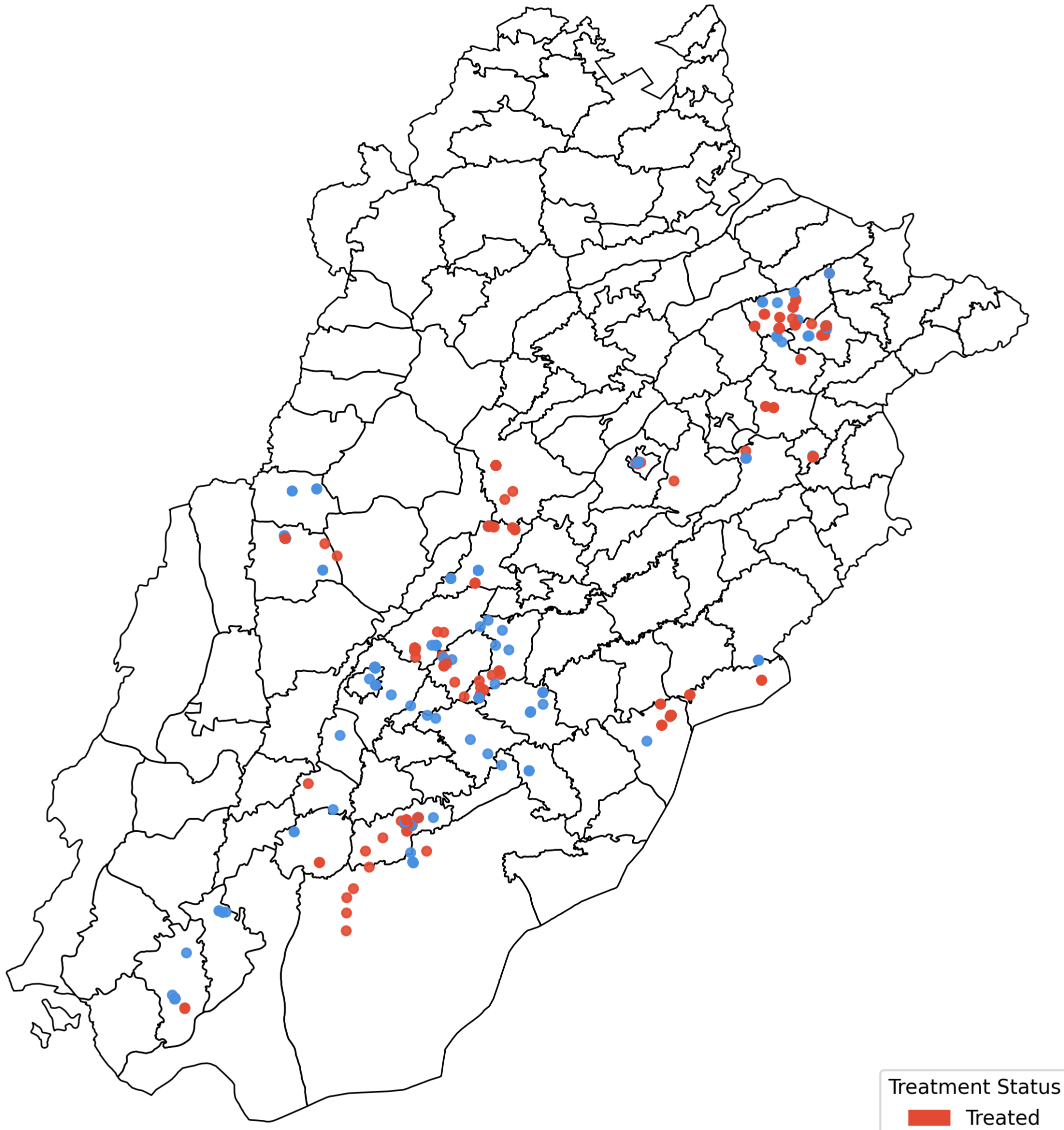
(b) Price Support: $\mathcal{U}(300, 600]$



(c) Price Support: $\mathcal{U}(600, 900]$



(d) Price Support: $\mathcal{U}(900, 1200]$

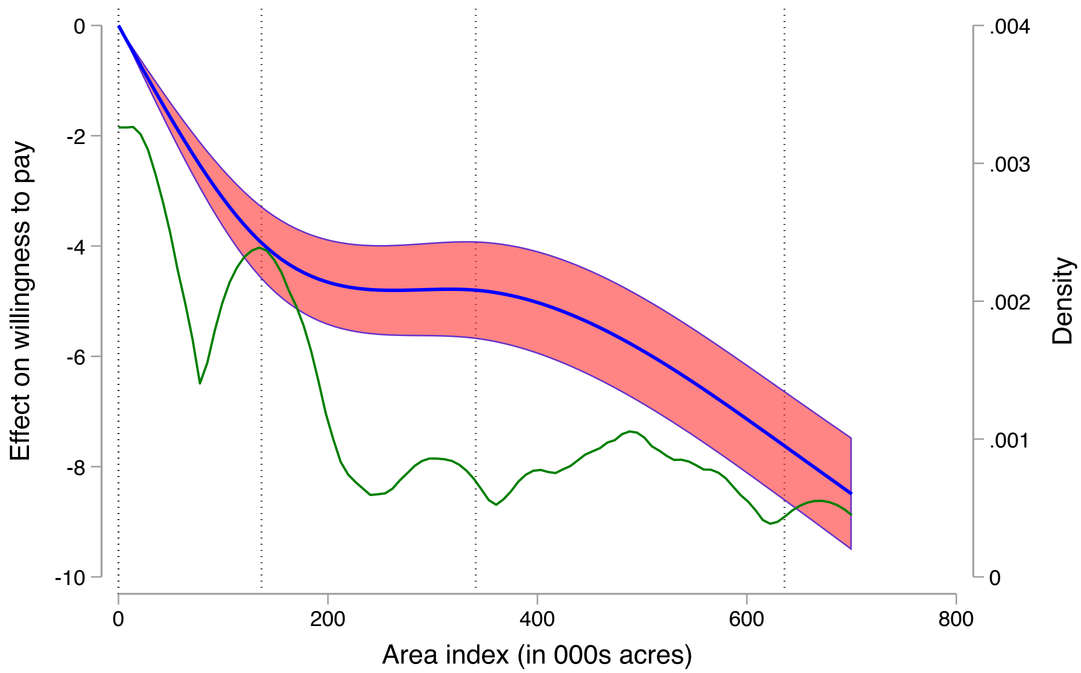


Note: Each dot represents a respondent, color-coded by their treatment status.

Figure B4: Spatial Distribution of Respondents in Treated and Control Groups

B.1 Basis risk

Figure B5: Allowing nonlinear relationships between basis risk and insurance WTP



Note: Figure plots the effect of basis risk on demand for crop insurance, allowing for a non-linear relationship. Specifically, we use restricted cubic splines with 5 knots (indicated by dashed lines). The point estimates (blue line) as well as the 95% confidence band are shown on the left y-axis. The density in index area is shown in green on the right axis

Table B3: Impact of Basis Risk on the Demand for Crop Insurance

	Willingess to Pay (in PKR)	
	(1)	(2)
Index Area (in 000'acres)	-0.0051***	-0.0051***
	(0.00082)	(0.00082)
2nd quartile risk aversion	0.47**	
	(0.21)	
3rd quartile risk aversion	0.13	
	(0.27)	
4th quartile risk aversion	0.46*	
	(0.23)	
2nd quintile risk aversion		0.64**
		(0.28)
3rd quintile risk aversion		0.43*
		(0.22)
4th quintile risk aversion		0.40*
		(0.23)
5th quintile risk aversion		0.23
		(0.26)
R^2	0.25	0.25
# of Individual-Contract Pairs	3465	3465
Controls	✓	✓
Contract FE	✓	✓
Price FE	✓	✓
SE	Household	Household

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B4: Impact of Basis Risk on the Demand for Crop Insurance

	WTP (in PKR)				
	(1)	(2)	(3)	(4)	(5)
Index Area (in 000'acres)	-0.88***	-0.50***	-0.46***	-0.64***	-0.61***
	(0.063)	(0.069)	(0.12)	(0.072)	(0.083)
Index Area × Knows Insurance (0/1)		-0.067*			
		(0.035)			
Index Area × Land Owned (%)			-0.075		
			(0.092)		
Index Area × Subj. Prob. of Payout				0.27***	
				(0.082)	
Time Preference					5.16
					(38.4)
RRA					6.31
					(11.9)
EIS					-0.91
					(0.99)
Outcome mean:	292.14	292.14	292.14	292.46	286.45
Index area mean:	868.92	868.92	868.92	865.79	856.85
N (# of Individual × Contract)	5310	5310	5310	5283	3462
Controls		✓	✓	✓	✓
Contract Type FE	✓	✓	✓	✓	✓
Price Support FE	✓	✓	✓	✓	✓
SE	Household	Household	Household	Household	Household
R^2	0.043	0.25	0.25	0.25	0.24

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B5: Impact of Basis Risk on the Demand for Crop Insurance

	WTP > 0 (Binary)				
	(1)	(2)	(3)	(4)	(5)
Index Area (in 000'acres)	-0.0014***	-0.00063***	-0.00049***	-0.00084***	-0.00065***
	(0.000081)	(0.000087)	(0.00013)	(0.000092)	(0.00010)
Index Area × Knows Insurance (0/1)		-0.000093*			
		(0.000048)			
Index Area × Land Owned (%)			-0.00019*		
			(0.00010)		
Index Area × Subj. Prob. of Payout				0.00042***	
				(0.000096)	
Time Preference					0.011
					(0.045)
RRA					0.032**
					(0.014)
EIS					-0.0025**
					(0.00100)
Outcome mean:	.57	.57	.57	.57	.6
Index area mean:	868.92	868.92	868.92	865.79	856.85
N (# of Individual × Contract)	5310	5310	5310	5283	3462
Controls		✓	✓	✓	✓
Contract Type FE	✓	✓	✓	✓	✓
Price Support FE	✓	✓	✓	✓	✓
SE	Household	Household	Household	Household	Household
R^2	0.091	0.27	0.27	0.27	0.24

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B6: Impact of Basis Risk on the Demand for Crop Insurance

	WTP (arcsinh)				
	(1)	(2)	(3)	(4)	(5)
Index Area (in 000'acres)	-0.00060***	-0.000087	-0.00020***	-0.00048***	-0.00028***
	(0.000044)	(0.00019)	(0.000065)	(0.000068)	(0.000058)
Index Area × Land Owned (%)		-0.00023			
		(0.00018)			
Index Area × Knows Insurance (0/1)			-0.00019***		
			(0.000066)		
Index Area × Subj. Prob. of Payout				0.00043***	
				(0.00013)	
Time Preference					0.14
					(0.32)
RRA					0.18*
					(0.100)
EIS					-0.015**
					(0.0073)
Outcome mean:	3.7	3.7	3.7	3.7	1
Index area mean:	876.28	868.92	876.28	873.2	867.91
N (# of Individual × Contract)	5310	5310	5310	5283	3462
Controls		✓	✓	✓	✓
Contract Type FE	✓	✓	✓	✓	✓
Price Support FE	✓	✓	✓	✓	✓
SE	Household	Household	Household	Household	Household
R^2	0.048	0.27	0.27	0.27	0.24

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * p<0.10, ** p<0.05, *** p<0.01.

Table B7: Impact of Basis Risk on the Demand for Crop Insurance

	WTP (arcsinh)				
	(1)	(2)	(3)	(4)	(5)
Yield Correlation	5.49***	2.93***	3.86***	2.32***	2.06***
	(0.63)	(0.58)	(0.65)	(0.60)	(0.69)
Yield Correlation × Knows Insurance (0/1)		0.041			
		(0.13)			
Yield Correlation × Land Owned (%)			-0.96***		
			(0.32)		
Yield Correlation × Subj. Prob. of Payout				1.41***	
				(0.30)	
Time Preference					0.14
					(0.32)
RRA					0.18*
					(0.10)
EIS					-0.016**
					(0.0074)
Outcome mean:	3.7	3.7	3.7	3.7	3.87
Mean Yield Correlation:	.33	.33	.33	.33	.33
N (# of Individual × Contract)	5310	5310	5310	5283	3462
Controls		✓	✓	✓	✓
Contract Type FE	✓	✓	✓	✓	✓
Price Support FE	✓	✓	✓	✓	✓
SE	Household	Household	Household	Household	Household
R^2	0.027	0.27	0.27	0.27	0.24

Notes: This table presents the impact of basis risk on the willingness to pay. The results are restricted to farmers who are part of the main sample. The control variables include: age, subsistence, irrigation sources, number of household members working on the farm, years of schooling, risk, measure of confidence (rain 23, rain 24, temp 23, temp 24), saving rate (in percent), consumption expenditure (5 months), total sources of income (last 12 months), as well as binary indicators for whether respondents fully understand the insurance scheme, know about insurance, took loan, owned any livestock, find it easier to negotiate with aarti, and grew cotton in Kharif 24. Standard errors in parentheses. Statistical significance is indicated by * $p<0.10$, ** $p<0.05$, *** $p<0.01$.