# Impacts of an innovative credit-insurance bundle for smallholder farmers: Evidence from a cluster randomized trial in Odisha, India

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**Abstract**

Smallholder farmers often lack documented land rights to serve as collateral for formal loans, with livelihoods inextricably linked to weather conditions. Resulting credit and risk constraints prevent them from investing in their farms. We implemented a randomized evaluation of KhetScore, an innovative credit scoring methodology that uses remote sensing to unlock credit and insurance for smallholders including landless farmers in Odisha, a state in eastern India. In our treatment group, where we offered KhetScore loans and insurance, farmers - and especially women - were more likely to be insured and borrow from formal sources without substituting formal for informal loans. Despite increased borrowing, treated households faced less difficulty in repaying loans, suggesting that insured KhetScore loans transferred risk and eased the burden of repayment. Moreover, the treatment enhanced agricultural profitability by increasing revenues during the monsoon season and reducing costs in the dry season. Positive and significant effects are found among both farmers with unconstrained baseline credit access, and quantity-rationed farmers, suggesting that KhetScore helps address supply-side credit constraints. Finally, the treatment significantly enhanced women's empowerment and mental health. In conclusion, remote sensing-enabled financial products can substantially improve landless farmers' access to agricultural credit, risk management, resilience, and well-being.

*Keywords*: credit; insurance; gender parity; impact evaluation; India.

**JEL codes**: D13, O13, O16, Q14.

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## Section 1. Introduction

To combat hunger, poverty, and global food security challenges, it is crucial to reduce risk, improve liquidity, and encourage investments in agricultural productivity. Because agriculture is inherently risky, smallholder farmers often lack the funds to expand their operations or invest in profitable technologies and inputs. For smallholders with limited land holdings, formal financial services like credit and insurance are often considered cost-prohibitive due to high transaction and monitoring costs, along with limited available data on these farmers to identify the risks of insuring or lending to these farmers. For instance, lacking documented land rights or lacking the necessary collateral limits potential borrowers' access to formal credit (Higgins et al., 2018), and consequently potential borrowers are involuntarily limited in their borrowing, resulting in efficiency losses and potential entrapment in a low productivity equilibrium (Croppenstedt et al., 2013). Even when individuals may have access to formal credit, credit markets can be in a disequilibrium in which lenders restrict potential borrowers' access to their desired level of borrowed funds to finance agricultural investments (Stiglitz and Weiss, 1981). In other cases, risk averse borrowers may voluntarily withdraw from the credit market, often because they are afraid of losing their collateral if there is an adverse calamity and they are unable to repay the loan. Such risk rationing (Boucher et al., 2008) occurs in any situation in which the lender shifts so much contract risk onto the borrower (in the form of excessive collateral requirements, high interest rates, unfavorable repayment terms, etc.) that the borrower voluntarily opts out of the credit market, even when otherwise qualifying for loans of a desired size.

One way to potentially overcome both types of credit rationing and expand investments in agriculture is through agricultural insurance. Yet, the challenges with agricultural insurance are well known (e.g., Hazell et al., 1986; Binswanger-Mkhize, 2012; Carter et al., 2017; Kramer et al., 2022), namely high costs associated with monitoring and assessing losses, resulting in high administrative loads; informational asymmetries manifesting as both adverse selection and moral hazard; the highly covariate nature of production risks; and a mismatch between insurance demand (which is highest among wealthier farmers) and who would actually benefit from risk transfers (poor farmers without the ability to self-insure). Although index-based insurance programs promoted to address some of these challenges have their own shortcomings, they have recently been able to achieve large scales by leveraging remote sensing, for instance to predict livestock mortality (Chantarat et al., 2013) or estimate food insecurity and humanitarian response costs, enabling risk pooling and drought insurance for countries (Kramer et al., 2020). However, to harness the full potential of remote sensing, it is essential to deepen our understanding of the extent to which it can enhance rural credit access, help smallholders manage agricultural risks (Benami et al., 2021), and improve targeted populations' wellbeing and livelihoods.

This evaluation assesses the impacts of KhetScore—a novel credit scoring method that generates credit scores using remote sensing and crop analytics—on farmers' access to credit and insurance, investments in agriculture, incomes, food security and wellbeing. KhetScore was designed to reduce transaction costs and overcome information asymmetries and documentation requirements in the provision of financial instruments for marginal landless farmers. Therefore, the evaluation pays particular attention to gender and baseline credit rationing status, conditions that have historically been associated with limited credit access and utilization. In the Indian context, female farmers frequently lack documented land rights required by formal lenders as a condition for qualifying for a loan. KhetScore aims to precisely address this issue by producing a lens into the production and profitability potential of a plot of land regardless of who holds the title to that plot. Further, KhetScore loans are bundled with insurance, which reduces both the need for collateral to secure a loan and the risk of collateral loss, since the insurance component could compensate the lender in the event of a catastrophic hazard that destroys a farmer's crop.

Consequently, there is great potential for this kind of product to ease both supply-side rationing on the part of the lender and demand-side rationing on the part of the potential borrower.

We implemented a cluster randomized trial with about 1,800 potential KhetScore clients from 58 villages in the district of Jajpur in eastern Odisha. These 58 villages were randomized into a treatment arm (29 villages), where farmers were offered KhetScore loans bundled with insurance to protect them from the risk of crop failure, and a control arm (29 villages), where farmers were not offered loans based on the KhetScore credit scoring methodology but may have accessed other sources of credit. Both KhetScore loans and crop insurance offered in the treatment arm leverage recent innovations in remote sensing, by monitoring crops using satellite imagery and smartphone pictures, respectively. We collected baseline and endline survey data on access to credit and insurance, investments in agriculture, farm incomes, women's empowerment, and mental health for all potential clients and their spouses. At baseline, women expressed lower demand for credit, but they reported more often than men that introducing alternative credit scoring approaches (such as those similar to the KhetScore approach using remotely sensed metrics of crop production potential) and bundling with insurance would make them both more likely to apply for loans more interested in borrowing larger amounts (Kramer et al., 2021).

In this paper, we find beneficial impacts of offering farmers KhetScore loans bundled with insurance over a wide range of outcomes, including financial inclusion, agricultural, gender parity, and mental health outcomes. In particular, the evaluation demonstrates the potential for this novel financial product to have transformative effects on the rural economy by strengthening financial literacy, improving credit and insurance uptake, increasing farm profits, enhancing women's empowerment, and easing some of the psychological and emotional health stresses that so often accompany near-subsistence agriculture.

The contributions of this paper are threefold. First, we demonstrate that this kind of credit and insurance bundle – and particularly one that determines an applicant's creditworthiness not based on traditional metrics but based on a metric using emergent digital technologies to determine production and profit potential – has a beneficial impact on crowding in marginalized groups into financial markets and improving their overall experience with credit. This pertains both to individuals who might have been credit-rationed at baseline, as well as women, who are typically excluded from credit markets because they often lack the documented land rights required by lenders as a condition for obtaining a loan. Not only do treated households from these disadvantaged groups take up loans at an accelerated pace compared to their counterparts in the control villages, but they also reported an increase in borrowing from formal sources and a decrease in borrowing from informal sources, therein largely increasing the extent to which they are included in the formal financial sector. We also demonstrate that this kind of credit and insurance bundle comes with terms that borrowers find especially favorable, as there is a significant reduction in the proportion of borrowers who reported difficulties in repaying their loans, and these effects persist even among members of these groups who might otherwise face financial difficulties.

Second, we contribute to the evidence on strategies to alleviate constraints faced by smallholder farmers to increase their agricultural output and productivity. In particular, local average treatment effects indicate that those farm households that received KhetScore loans bundled with insurance attained higher revenue per acre and higher profit per acre than other households. Among those that borrowed funds, revenues and profits per acre were more than INR 7,800 (USD 105) and INR 9,000 (USD 121) higher than among farmers in the control group. The effects are largest among those farmers who were not credit rationed at the time of the project baseline, but the beneficial impacts carry over to those farmers who were quantity-rationed at baseline, implying that this product does alleviate supply-side constraints to borrowing that could enhance agricultural livelihoods.

Finally, we demonstrate that this innovative credit and insurance bundle has the potential to significantly improve women's empowerment, thereby adding to the literature on improving gender parity in agriculture through financial inclusion. Although we find positive intention-to-treat effects across several different domains of women's empowerment, it is worth noting in particular that those women who were the primary clients (with the loan and insurance bundle taken out in their name) reported a significant increase in their contributions to household financial decisions, especially those related to the decisions whether to borrow and how to use borrowed funds. Although women's contributions in these decision-making domains remain relatively low, these beneficial impacts hint at this products' potential to alter intrahousehold dynamics and improve gender parity in financial matters.

The remainder of this paper is structured as follows. The next section describes our evaluation methods, including the design and timeline of the evaluation, sampling and data collection methods, and our empirical specification. The next section describes findings of this impact evaluation, at both the aggregate level and for male versus female farmers. The final section concludes.

## Section 2. Methods

### *2.1 Context and intervention*

The study was conducted in Odisha, a state in eastern India, which covers over 1.56 million hectares of land, or 4.7% of India's total land mass. The state has four geographical regions: the Northern plateau, Central River basins, Eastern Hills, and Coastal Plains. This diversity creates a rich set of agro-climatic zones, including both low-lying coastal areas along the Bay of Bengal (exposed to tropical cyclones and frequent prolonged floods) and rainfed uplands that (exposed to moisture stress due to variability in rainfall). Farming in Odisha is hence a vulnerable activity exposed to many extreme weather risks. Almost every other year, a part of Odisha is hit by natural calamities.

Despite these risks to the agricultural sector, Odisha is one of the largest producers of food grain, and particularly paddy rice, with around 55 percent of the area under cultivation used for food grain production, and around 49% of the total workforce being dependent on agriculture. Along with much of India, there are two growing seasons in Odisha: the summer monsoon (Kharif) season, during which farmers mainly produce paddy rice, and the winter (Rabi) season, during which many farmers have historically their land fallow due to a dearth of rainfall and limited availability of supplemental irrigation. However, the past few years have observed an increase in the share of Rabi production, and particularly of high-value crops like pulses and vegetables, no doubt at least partly attributable to a 49% increase in the area under irrigation. Promoting investments in the cultivation of high-value crops during the Rabi season is considered an important channel to transform agricultural livelihoods in the state. Credit and insurance are key in this regard.

We implemented this study in two blocks of Jajpur, a district in Odisha's low-lying coastal plains (Figure 2), where tropical cyclones and frequent prolonged floods form the main production risks in agriculture. In this district, agricultural activities are one of the primary sources of income, with paddy being the dominant crop grown. Irrigation is available in Jajpur due to the vicinity of the *Mahanadi*, the largest river of the state. This creates opportunities for farmers to expand production during the Rabi season, but credit and risk are often cited as a primary reason for not investing in crop production during this season. Intercropping is not common, making it suitable for applications that use remote sensing for crop monitoring. Despite relatively higher literacy and education levels compared to farmers in other districts, Jajpur has a large concentration of sharecroppers and marginalized landless farmers who fall outside the purview of state-sponsored credit and insurance schemes (including the Pradhan Mantri Fasal Bima Yojana, or PMFBY), since they lack documented land rights required by these schemes.

To address this challenge, our implementing partner, Dvara E-Registry (DER), developed KhetScore, an innovation that uses remote sensing to unlock credit and insurance for small and marginal farmers. To provide KhetScore loans, DER (i) digitizes information on a farmer's land parcels, regardless of whether a farmer owns, rents, or sharecrops the land, using georeferenced smartphone images for verification, (ii) creates plot-level agricultural credit scores by estimating past and current productivity from satellite imagery, (iii) provides loans for farmers with sufficiently high credit scores, and, (iv) adds on crop insurance to de-risk these loans, using smartphone images taken at regular intervals throughout the crop season to verify any claims of crop damage due to extreme weather or other natural hazards such as pests and disease.

One of the main aims of the KhetScore credit scoring methodology is to unlock credit for individuals who do not have a credit score with formal credit bureaus. The score is an index ranging between 0 and 100 based on six variables with different weights, including productivity (40%), changes in crop health (20%), moisture (15%), past instances of mechanical damage (13%), nutrient availability (7%), and the area of cultivation (5%). A farmer's KhetScore needs to be at least 40, which is considered to indicate reasonable creditworthiness, in order to be eligible for a loan. Applications may however still be rejected if an applicant's identification card (Aadhar) does not match bank account details, if the applicant has a poor (instead of no) credit report with the credit bureau, or if the farmer did not cultivate anything for three consecutive years during the agricultural season (kharif or rabi) for which the farmer is requesting a loan.

KhetScore loans have been designed around agricultural operations, though the loans are disbursed as cash payments rather than input vouchers. The size of the loan is based on the cost of paddy production for an acre of land, which is an estimated 30,000 Indian Rupees (INR) (USD 400). The interest rate on these loans is 14%, well below the market interest rate of 24%. Repayment is done in multiple installments, with two to three payments before harvest, and a final bullet repayment soon after harvest. Future loans are provided to farmers subject to timely repayment of prior loans and availability of funds, but farmers are granted a certain degree of flexibility in loan repayment, to maximize the chances that a farmer can repay. Though there is a nominal penalty (INR 5 per day) for late repayment, they can be granted additional time to repay the loan in case they have a legitimate excuse for being unable to repay. In the rare case that the farmer does not repay a loan, DER staff work with the farmer for proper follow up and counselling. Repayment rates were very high, at 83%.

Farmers with approved applications receive the loan, bundled with multi-peril crop insurance for the full value of the loan. The insurance policy covers farmers for any visible crop damage from natural causes, including excess rainfall, hailstorms, winds, animal attacks, pests and diseases, landslides, and localized unseasonal rainfall. Several of these perils are characteristic of cyclonic activities that regularly impact coastal Odisha. To verify claims of crop damage and ensure adequate crop management leading up to the damage, DER staff take bi-weekly images of insured land until the time of harvesting. For farmers who report damage, claims are calculated by agricultural experts at DER who review the images to declare a percentage of loss. This loss assessment determines the insurance payout, which is then sent into the famer's bank account.

During a farmer profiling meeting, DER provided product trainings, introducing farmers to KhetScore and the insurance product. After that, farmers could apply for a KhetScore loan. Farmers interested in a KhetScore loan needed the approval of at least one other family member, typically their spouse, and this person would be a co-signer on the loan. Any farmer with a KhetScore loan was also enrolled in insurance, with premiums fully subsidized in this initial piloting phase. Farmers who did not apply for a KhetScore loan, or whose applications were not granted, could still apply for the insurance product separately.

### *2.2 Design and timeline*

To evaluate the impacts of these financial instruments, we implemented a cluster randomized trial with about 1,800 potential KhetScore clients from 58 villages of two blocks in Jajpur, selected due to their large population of marginalized landless farmers and DER's existing presence in these areas. DER covered all villages in these two blocks, except for those deemed unfeasible for lending operations due to the high risk of flooding. Including these villages would have increased insurance costs to unsustainable levels and potentially jeopardized the ability of farmers in these villages to repay their loans.

We randomized all 58 villages into a treatment arm (29 villages), where farmers were offered the KhetScore loans bundled with insurance, and a control arm (29 villages), where DER did not offer any loans or insurance products (although farmers may have accessed other sources of credit and insurance, such as the national insurance scheme – if they could produce documented land rights and overcome the administrative hurdles that farmers face when enrolling in the scheme). The randomized trial was implemented over three consecutive seasons, including the Kharif seasons of 2021 and 2022, and the Rabi season of 2021/2022. A timeline of the study is provided in Figure  below.

### *2.3 Sampling and data collection*

Within each of the 58 study villages (including both treatment and control villages) DER organized farmer profiling meetings during which they compiled a list of prospective clients who attended these meetings. This list serves as our sampling frame. Specifically, at baseline (at the end of 2020 through early 2021), we invited the full list of 1,872 farmers for a phone survey (in-person data collection was not possible due to COVID-19 related restrictions on mobility in Jajpur district). Based on power calculations, we aimed to survey at least 1,800 farmers at baseline. Assuming a 3% percent attrition rate from baseline to endline, this meant recruiting at least 1,854 clients through product meetings. Some of the farmers (62) invited for the phone survey were not reachable due to incorrect phone numbers or phones being switched off. Others (101) refused to consent to the interview. Consequently, we were able to survey 1,709 households.

The endline survey was conducted in person in November/December 2022, and by then, pandemic-related restrictions on mobility had been lifted. We aimed to re-survey all respondents at baseline, as well as one other family member of the opposite sex (usually the client's spouse, and typically a co-signer for loans issued by DER). Of the 1,709 clients surveyed at baseline, we were able to track and re-survey 1,621 clients (89.6%). We were able to identify and interview another family member for 1,294 of those respondents, for a total sample of 2,915 individuals.

Both baseline and endline surveys included modules to collect information about the respondent's demographics, household income, financial inclusion, credit practices, women's empowerment, insurance take-up and renewal, awareness and perceptions of insurance, income from insured crops, and women's mental health. Questions related to insurance take-up and renewal, awareness and perceptions of insurance, and income from insured crops, were asked to the primary client only. Questions about women's mental health were asked only to the female member of the household.[1] Other questions (related to demographics, household income,

[1] Our registered pre-analysis plan (study ID RIDIE-STUDY-ID-6110cd09b6003) indicates that we will also evaluate impacts on household food consumption and women's dietary diversity. These outcomes were included at the request of the project donor, to

financial inclusion, and credit practices) were asked to both respondents in each household. At baseline, we also included a series of questions to determine types of credit rationing in the sample. As alluded to previously, credit rationing frequently takes one of two specific varieties, namely quantity (supply-side) rationing or risk (demand-side) rationing. These are obviously not part of the vernacular for the average farmer in Odisha, so classifying individuals as being quantity rationed, risk rationed, or unconstrained (as it pertains to credit) requires some deduction.

In particular, the baseline included two questions that asked (1) how much the respondent needed to borrow to finance household activities, and (2) how much credit was actually granted. If these two sums were the same, the respondent was deemed to not be credit constrained. If the desired loan amount was less than the loan amount granted, the respondent was deemed to be quantity rationed, since this would indicate a supply-side limit on the amount the respondent could borrow. But there were also respondents who indicated that they did not borrow within the last 12 months, and a third question attempted to elicit the reasons (potentially multiple) why the respondent did not borrow in the previous 12 months. If the respondent indicated that they did not borrow because (a) the loan amount offered was insufficient, (b) they were deemed to not be creditworthy, or (c) they lacked sufficient capital to secure a loan, they were classified as quantity rationed, again because these barriers to borrowing stem from supply-side conditions. If, on the other hand, the respondent indicated that they did not borrow in the previous 12 months because (a) they were afraid of losing collateral, (b) the loan terms were not flexible enough, (c) the application costs were too high, or (d) there was a high interest rate, they were deemed to be risk rationed, since these constraints reflect demand-side considerations inhibiting borrowing.[2]

### *2.4 Empirical strategy*

To estimate intent-to-treat (ITT) effects, we use analysis of covariance (ANCOVA) estimators, in which endline values of dependent variables (outcomes) are regressed on a dummy variable indicating whether the farmer was in the treatment group, controlling for baseline values of the dependent variable and a matrix of covariates, with standard errors adjusted for the clustered nature of the experimental design (i.e., by village, since randomization was done at the village level).[3] Our base econometric specification will be the following:

$$Y_{ib,1} = \alpha + \beta Y_{ib,0} + \delta_1 T_{ib} + \sum_{j=1}^{J} \theta_j \mathbf{x}_{ijb,0} + \varepsilon_{ib} \tag{1}$$

where $Y_{ib,t}$ is the measure of outcome $Y$ for individual $i$ from block $b$ in period $t \in \{0,1\}$, with $t = 0$ and $t = 1$ indicating baseline and endline, respectively; $\mathbf{x}_{ijb,0}$ is a vector of covariates including block fixed effects to account for stratification and variables with statistically significant differences between the treatment versus control at the time of the baseline, as well as demographic controls from the endline survey (caste, literacy, age terciles, and the primary client's gender); $\varepsilon_{ib}$ is an identically distributed disturbance assumed to be independently distributed across villages, but correlated among members from the same village; and $T_{ib}$ is a binary variable equal to 1 if

track such measures among all funded projects. We have not included these outcomes in the impact evaluation presented in this manuscript, both because there were no meaningful impacts observed, but also because there is not an obvious causal mechanism by which we would have expected there to be observed impacts in the time frame of this evaluation.

[2] It should be noted that the risk aversion reflected in these conditions is not solely on the part of the (potential) borrower. High interest rates, inflexible loan terms, and high application costs are ways in which the lender can (or at least attempts to) transfer some of the contract risk on to the applicant, but ultimately it is the applicant that decides to voluntarily withdraw from the credit market due to these conditions.

[3] For some outcomes, we do not have baseline values to include in "pure" ANCOVA regressions. In such cases, we include baseline values of a close proxy in "pseudo"-ANCOVA regressions.

individual $i$ from village $b$ was from a village randomly selected as part of the treatment arm. This base specification will allow for us to estimate the average effect of the program in treatment villages (meaning that these are ITT effects).

In addition to this base specification, we will be interested in examining heterogeneous effects by (i) gender and (ii) baseline credit rationing status.[4] To do so, we will modify equation (1) and estimate one of the following two regressions:

$$Y_{ib,1} = \alpha + \beta Y_{ib,0} + \gamma Female_{ib} + \delta_1 T_{ib} + \delta_2 T_{ib} \times Female_{ib} + \sum_{j=1}^{J} \theta_j \mathbf{x}_{ijb,0} + \varepsilon_{ib} \quad (2)$$

$$Y_{ib,1} = \alpha + \beta Y_{ib,0} + \gamma_1 Q_{ib} + \gamma_2 R_{ib} + \delta_1 T_{ib} + \delta_2 T_{ib} \times Q_{ib} + \delta_3 T_{ib} \times R_{ib} + \sum_{j=1}^{J} \theta_j \mathbf{x}_{ijb,0} + \varepsilon_{ib} \quad (3)$$

where, in equation (2), $Female_{ib}$ is a binary variable equal to 1 if individual $i$ from village $b$ was a female (and 0 otherwise), and in equation , $Q_{ib}$ and $R_{ib}$ are binary variables equal to 1 if individual $i$ from village $b$ was quantity or risk rationed, respectively, at the time of project baseline (with unrationed individuals as the omitted category). In equation (2), $Female_{ib}$ is interacted with $T_{ib}$ to test whether the program had differential effects on male ($\delta_1$) and female respondents ($\delta_1 + \delta_2$) within the treatment group. In equation $Q_{ib}$ and $R_{ib}$ are each interacted with $T_{ib}$, allowing us to test whether the program had differential effects on unrationed ($\delta_1$), quantity-rationed ($\delta_1 + \delta_2$), or risk-rationed individuals ($\delta_1 + \delta_3$) within the treatment group.

For outcome measures related to women's mental health, we only have data on female respondents since these questions were only asked of female respondents. Further, these outcome measures were specified differently at the time of baseline and endline data collection, so there are no comparable baseline measures for these outcomes to be included in an ANCOVA regression. For these outcome variables, we therefore modify the regression equation by dropping $Y_{ib,0}$, reducing the estimator to a single-difference comparison of simple (conditional) differences between treated and control samples. However, as a unique feature of our data set, we have data not only on the client, but also on another household member who, in the case of households with KhetScore loans, would have co-signed on this loan. Consequently, we can still estimate effects separately for women in households where the primary client is male (meaning that the female is the "other household member") versus female (so that the female is the "client") and estimate a variation of equation (2):

$$Y_{ib,1} = \alpha + \gamma Other_{ib} + \delta_1 T_{ib} + \delta_2 T_{ib} \times Other_{ib} + \sum_{j=1}^{J} \theta_j \mathbf{x}_{ijb,0} + \varepsilon_{ib} \quad (3)$$

where all terms are as they were introduced before, though specifically pertaining to female respondents, and $Other_{ib}$ is a binary indicator equal to 1 if the respondent was classified as the "other household member" – implying she was not a DER client but his spouse. So, the ITT effect

[4] In our registered pre-analysis plan, we did not specify that we would explore heterogeneous impacts on the basis of baseline credit rationing status. This was a dimension of heterogeneity that was subsequently included based on conversations with participants in a research seminar given by one of the authors.

among DER's female clients is captured by $\delta_1$, and the spillover effects from DER's male client to his female household member is captured by $\delta_1 + \delta_2$.

Equations (1)-(3) estimate ITT effects, providing an estimate of overall impacts of offering loans and insurance based on the KhetScore credit-scoring methodology, regardless of whether a household took up the product. Assuming a positive correlation between take-up and the various outcomes of interest, these ITT effects will be a downward-biased measure of the beneficial impacts. They provide a conservative estimate of the overall program impacts and may be of greater interest to policymakers interested in the economywide impacts of the program, rather than just the effects on those households who took up KhetScore loans. Nevertheless, we also estimate impacts for those households in the sample that decided to take up these products if offered to them. We estimated local average treatment effects, or LATEs (Imbens and Angrist, 1994), by instrumenting for product take-up with random assignment to the treatment group.[5] For estimating heterogeneous LATEs, we instrument for the interaction between gender or credit rationing status and product take-up with an interaction between gender or credit rationing and random assignment to the treatment group.

For models in which the outcome variable is binary, a further complication arises in the case of the IV estimator for the LATE, namely that predicted probabilities from a linear probability model can be outside the unit interval (0,1), which can be especially pervasive in IV estimations with comparatively low compliance among the treatment group. To circumvent these challenges in estimating LATEs for the credit-insurance bundle described in the present paper, we implement a recursive bivariate probit estimator, which is appropriate for estimation scenarios in which (1) the outcome variable is binary, (2) the endogenous treatment is binary, and (3) the instrument is binary, as is the case with many of our outcomes, especially those related to credit and insurance take-up. Appendix A provides an overview of our estimation strategy using the recursive bivariate probit. To consider heterogeneous LATEs (i.e., by gender or by baseline credit rationing status), we estimate recursive bivariate probit models separately for the three subgroups and compute point estimates for LATEs for each subgroup, with corresponding 95 percent confidence intervals for these LATEs constructed using a nonparametric bootstrap.

## Section 3. Descriptive statistics

### *3.1. Summary statistics*

Table 1 provides summary statistics of 1,709 DER clients surveyed at baseline. About 70 percent of clients were female and an average respondent is around 42 years of age. About 85 percent know how to read and write, with 75 percent having completed at least primary education, and 25 percent having completed at least secondary education. Regarding caste or tribe membership, 36 percent clients belong to the Scheduled Castes, a tenth belong to the Scheduled Tribes, while another 18 percent belong to Other Backward Classes. More than half of households' annual income fall below INR 90,000 (USD 1,210) per year, or INR 247 per day, which puts a 2-member household below the poverty line of USD 2 per day. About 28 percent have an annual income

[5] If product take up is relatively low (indicating a non-trivial degree of non-compliance with assignment), the resulting LATE could over-state treatment effects among the treated. Consequently, IV LATE estimates can be considered as upper bound estimates of average treatment effects. In the case of a single endogenous variable (product take-up) and a single excluded instrument (random assignment), the F-statistic on the first stage regression is 44.09, so our identification strategy does not suffer from a weak instrument.

between INR 90,000 (USD 1,210) and INR 120,000 (USD 1,613), while only around 19 percent have an annual income of more than INR 120,000 (USD 1,613).

In terms of clients' experience with credit and crop insurance, half of the DER clients report having purchased on credit in the past 12 months and around 30 percent have borrowed money in the same period. An average client's desired loan size for the last season is INR 37,620 (USD 506). In contrast, insurance take-up rate is extremely low – only 3 percent have had crop insurance in the past, 1 percent currently have crop insurance, and less than 1 percent report having received pay-out from such insurance.

Regarding cultivation practices and agricultural outcomes, most clients (86 percent) cultivated in the most recent Kharif season while fewer (75 percent) did in the most recent Rabi season. An average household cultivates a total of 2 acres of land, with three quarters of households falling into the category small farmer households (cultivate 0-2.5 acres of land), 23 percent being marginal farmer households (cultivate 2.5-5 acres of land), and only 2 percent being defined as medium farmer households (cultivate 5-10 acres of land). Virtually all clients are paddy rice farmers and 26 percent have experienced crop damages and loss. An average household reports making a total agricultural revenue of INR 22,950 (USD 308) per acre, incurring a total cost of INR 13,773 (USD 185) per acre, and earning a profit of INR 9,177 (USD 123) per acre (excluding the cost of own labor).

Panel D of and summarize the distribution of DER clients' credit rationing status at baseline. Across both treatment and control arms, the plurality of clients responded to survey questions in such a way that they were classified as quantity rationed (48 percent of clients in the control group and 54 percent in the treatment group), having faced supply-side constraints in accessing their desired level of credit. They could potentially benefit from the credit-insurance bundle to the extent that the KhetScore credit scoring methodology circumvents some of the other, more traditional means by which individuals could qualify for loans (e.g., credit reports with formal credit bureaus or documentation of land rights), or to the extent that the accompanying insurance component eases lenders' concerns about borrowers' potential to repay loans, especially in the event of near-catastrophic crop losses that might otherwise impinge upon their repayment ability. Roughly another 30 percent across both treatment and control were classified as risk rationed, opting out of loans because of lenders transferring contract risk onto potential borrowers in the form of higher interest rates, fees, or collateral burdens. The bundled insurance component may benefit them by absorbing some of that contract risk and ameliorating some of these other less attractive terms. Finally, about 25 percent of farmers in the control group and 16 percent of farmers in the treatment group were neither quantity nor risk rationed at the time of project baseline, and consequently are identified as unconstrained.

### *3.2. Balance across treatments*

Summary statistics for the treatment and the control group are presented in columns 3 to 6 in Table 1, and the differences between treatment and control are shown in column 7. We find that overall, variables are well balanced across treatment and control with only a few exceptions, suggesting that randomization resulted in two comparable samples. Imbalanced variables include the following: the percentage of DER clients that belong to the General Caste (31 percent in the control group versus 42 percent in the treatment group), the percentage of DER clients that belong to the Scheduled Castes (43 percent in the control group versus 29 percent in the treatment group), the percentage of clients purchasing goods and services on credit in the past 12 months (42 percent in the control group versus 56 percent in the treatment group), the percentage of farmers that cultivated in the most recent Rabi season (82 percent in the control group versus 68 percent in the treatment group), profits per acre (INR 7,615 (USD 102) in the control group versus INR 10,891 (USD 146) in the treatment group), and the percentage of clients that are credit unconstrained (24 percent in the control group versus 16 percent in the treatment group). We control for these differences in our impact evaluation estimates.

### *3.3. Uptake of the intervention*

Table 2 reports monitoring and evaluation (M&E) data concerning the uptake of the intervention. Preceding each season, enrollment initiatives occurred one to two months in advance. Dedicated personnel from DER personally contacted all eligible farmers in each treatment village to encourage them to apply for the KhetScore product. Column (1) indicates, per season, the number of farmers who applied for KhetScore loans. Column (2) denotes the count of farmers eligible for KhetScore and who had the loan disbursed to their bank accounts. Column (3) represents the number of farmers enrolled in insurance during the respective seasons (regardless of loan uptake), and column (4) indicates the count of farmers who received payouts for those seasons.

On average, approximately 28% of farmers offered KhetScore loans applied for it each season. Initially, uptake was subdued due to various challenges. COVID-19 lockdowns necessitated DER staff to contact farmers via phone, leading to issues concerning farmer availability, low mobile penetration in Odisha, incorrect contact information, network connectivity problems, and establishing rapport. Over time, these challenges were mitigated by transitioning to in-person visits, facilitated by continued engagement with farmers over multiple seasons. Additionally, financing KhetScore loans during the pandemic was challenging as institutional lenders were cautious about microloans. However, DER demonstrated the viability of its lending model using the relatively small number of initial KhetScore loans, securing additional funding for subsequent seasons. Consequently, there was a progressive increase in the number of farmers applying for, receiving, and enrolling in insurance alongside KhetScore loans.

## Section 4. Results

### *4.1 Impacts of KhetScore loans*

We first examine the impacts of the program on credit uptake (Table 4) and report ITT effects of random assignment to KhetScore treatment group and LATEs of the uptake of KhetScore loan-insurance bundle based on both instrumental variables (IV) and recursive bivariate probit regressions. As previously mentioned, IV methods are likely to result in overestimation of the LATEs when there is significant noncompliance with treatment status among those randomly assigned to be a part of the treatment group. Consequently, our preferred LATE estimates are based on the recursive bivariate probit estimates.

Starting with the overall impact of the KhetScore program (Panel A), although there is limited evidence that the program had an overall effect on increasing credit uptake, there is compelling evidence that the KhetScore loan-insurance bundle is effective in encouraging borrowing from formal sources and deterring borrowing from informal sources, which are typically associated with higher interest rates and less favorable loan terms. The KhetScore bundle also appears to reduce difficulties in repayment, which 76 percent of respondent in the control villages report having trouble with.[7] The LATEs are qualitatively similar to the ITT estimates, though there are some

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[7] While not specific to the credit-scoring methodology per se, it should be noted that the loans that were offered as part of this project required repayments in instalments rather than in a single lump sum, which is often the case for agricultural loans, or rather than weekly instalments, which often applies to microfinance loans. Anecdotal evidence suggests that borrowers especially liked this

important quantitative differences that merit some discussion. Participants from treatment villages who took up a KhetScore loan-insurance bundle increased their borrowing from formal sources by over 51 percentage points, compared with only about a 20 percentage point increase among the broader group of households randomly assigned to the treatment (columns 6 and 4). At the same time, complying members of treatment villages that took up the product only reduced their borrowing from informal sources by about 12 percentage points, compared with a reduction of 20 percentage points among the broader treatment group (columns 9 and 7). Finally, complying participants report a 20 percentage point reduction in facing difficulties of repayment, compared to a huge 56 percentage point decrease among those assigned to the treatment group (columns 12 and 10).

In Panel B, we examine heterogeneous effects among male and female clients. LATEs among male clients that took a KhetScore loan suggest that there is a small (3 percentage point, column 9) reduction in borrowing from informal sources, with a sizable (more than 50 percentage points, column 6) increase in borrowing from formal sources, revealing that many male clients continue to borrow from both formal and informal sources. This contrasts with the ITT effects, where we observe 17 percentage point increase in formal borrowing and a 26-percentage point reduction in informal borrowing (columns 4 and 6), which suggested a substitution of formal for informal borrowing. Among female clients, LATE estimates show that there is a sizeable (23 percentage point, column 9) reduction in borrowing from informal sources and a large (42 percentage point, column 6) increase in formal borrowing, providing compelling evidence that the program crowded-in borrowing among females. Additionally, LATEs reveal that both men and women clients were about 20 percentage points less likely to have faced difficulty in repaying their loans (column 12), though they are smaller in magnitude than the respective ITT effect estimates, which show 50 and 60 percentage point reductions among male and female, respectively (column 10).

In Panel C, we explore heterogeneity in program impacts among clients based on their baseline credit rationing status. Although we do not find any statistically significant that the program increased overall credit uptake (column 1), we generally find that the program facilitated a substitution of formal for informal credit among unconstrained, quantity rationed, and risk rationed members of treatment villages, with the magnitude of effects being mostly indistinguishable across rationing status (columns 4 and 7). Consequently, although quantity- and risk-rationed borrowers may not disproportionately benefit from the KhetScore credit scoring methodology, the results clearly suggest that they benefit at least as much as those individuals who were not credit rationed – and who presumably would have had a more secure financial standing – at the time of the project baseline. Both quantity- and risk-rationed individuals from treatment villages reported facing difficulty in repaying their loans with a much lower frequency than members of the control group (column 10), and despite the point estimate on this effect being greater among those individuals who were not credit constrained at baseline, the effects are not statistically distinguishable from one another.

Table 5 presents the results on the impacts of the program on outcomes pertaining to insurance, including insurance uptake, insurance renewal, and financial literacy (i.e., understanding of the terms and conditions of crop insurance measured via an insurance knowledge score) over the course of the project. We find overall positive and statistically significant effects of the program on insurance outcomes. Assignment to treatment villages increased the likelihood of taking up insurance at least once during the study period by more than 60 percentage points (Panel A, column 1), and the treatment effect does not vary across gender or rationing status. Our preferred

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feature of the loans, though some borrowers may have had to work off-farm to be able to pay off the first two or three instalments, which are due during the season before the harvest. This did not, evidently, have a detrimental effect on how they perceived their abilities to repay their loans.

recursive bivariate probit LATE estimates show that purchasing the KhetScore loan-insurance bundle led to a smaller 23-percentage point increase in insurance take-up (Panel A, column 3), suggesting that some of the benefits of program placement in treatment villages spilled over onto participants who did not necessarily take up this specific KhetScore product.

Moving on, the likelihood to renew insurance coverage increased by nearly 30 percentage points among participants in the treatment village who had previously purchased insurance before (Panel A, column 4), and the effect is found to be mainly driven by women, whose insurance renewal increased by nearly 60 percentage points (Panel B, column 4), though this gender difference is no longer statistically significant among those who took up the product in our preferred LATEs specification (Panel B, column 6).

Lastly, random assignment to treatment group increased the number of correct answers to a total of six crop insurance questions by 0.5 (Panel A, column 7). Additionally, our LATE estimate based on IV reveal that those who took up the product answered 1.6 more crop insurance questions correctly (Panel A, column 8), which suggest a sizable improvement in the understanding of the details of crop insurance among those who took up the KhetScore loan. Turning to heterogenous treatment effects by gender, the effect on insurance knowledge is largely observed among men, whereas there are wide variations in estimates among women that make the point estimates not statistically significant (Panel B, columns 7 and 8). We do not observe significant differences in treatment effects on insurance outcomes among participants with different rationing status at baseline, which further provides evidence that the KhetScore product does not discriminate against farmers facing supply- or demand-side constraints.

In Table 6 and Table 7, we present results on the ITT and LATE estimates of the KhetScore program on a series of agricultural outcomes during kharif (monsoon) and rabi (winter) seasons, respectively. LATE results are qualitatively similar to ITT estimates, but, as would generally be expected, they are of considerably larger magnitude, suggesting that the beneficial effects of the KhetScore credit-insurance bundle are primarily experienced among those who directly benefited from the loans. Here we mainly discuss the ITT results. Starting with the kharif season in Table 5, although we do not find any evidence that farmers in the treatment group expanded their area cultivated (Panel A, column 1), revenues per acre in the treatment group were nearly INR 2,000 (USD 27) greater than those in the control group (Panel A, column 3). The effects on revenues per acre are slightly more pronounced among male clients, with male clients observing a statistically significant INR 2,400 (USD 32) increase in revenues per acre, compared with a statistically insignificant increase of only INR 1,450 (USD 19) per acre among women clients (Panel B, column 3). The program also appears to have had beneficial impacts among those who were previously quantity (supply-side) rationed or unrationed in their access to credit, as revenues per acre increased by approximately INR 2,200 (USD 30) and INR 2,000 (USD 27) per acre, respectively (Panel C, column 3). There is also evidence that agricultural profits increased by a little more than INR 2,000 (USD 27) per acre among farmers in the treatment group (Panel A, column 9), more than doubling profits in the control group, and the magnitude of the effect is similar among women and men (Panel B, column 9). This positive effect is experienced by farmers regardless of their baseline credit rationing status (Panel C, column 10), with unconstrained farmers experiencing the largest boost in profits of about INR 2,700 (USD 36) per acre, followed by quantity rationed (INR 2,400/ USD 32 per acre) and risk rationed (INR 2,220/USD 30 per acre). In Table A1 in Appendix B, we report the results of a series of regressions

Turning to the rabi season in Table 6, while we do not observe any increase in the proportion of farmers cultivating in the rabi season (Panel A, column 1), treatment households increased their cultivated area by 0.5 acres, or 31% of the average 1.7 acres cultivated during the rabi season in the control group (Panel A, column 4).[8] The expansion of land cultivated during the rabi season was considerably higher for women (0.6 acres) than for men (0.4 acres; Panel B, column 4), and among farmers who had previously been credit constrained - previously quantity and risk rationed farmers increased their rabi area by more than 0.65 and 0.55 acres, respectively (Panel C, column 4). The total cost of production per acre fell by about INR 3,200 (USD 43) among farmers in the treatment group, perhaps as treatment farmers generated economies of scale (Panel A, column 8), and women saw a greater decrease than men (Panel B, column 8). We also observe households in the treatment group having significantly higher agricultural profits per acre of INR 14,260, nearly offsetting the INR 19,000 (USD 255) losses suffered by farmers in the control group.[9] All told, results in Panel C imply that this product may alleviate both supply-side and demand-side constraints to borrowing that could enhance agricultural livelihoods (Panel C).

In Table 8, we present results on the effect of the treatment on gender parity outcomes, especially intra-household gender dynamics, among DER clients (Panel A) and non-client family members (Panel B) through exploiting whether they (1) contribute to household borrowing decisions, (2) contribute to household decisions about how to spend borrowed money, (3) give input on household livelihood decisions, (4) exercise control over uses of income, and (5) own land and/or any three assets. We find sizable and statistically significant improvements in these five empowerment indicators among treatment households, primarily among women, though there is considerable heterogeneity in whether the significant effects are driven by female DER clients or non-client female household members. For female DER clients, the treatment improves their ability to contribute to household decisions around borrowing and the use of borrowed funds, while other female household members (i.e., female partners of male clients) gain the ability to provide input on household livelihood decisions and control over household income. As for asset ownership, we observe that male DER clients and more so their female family members in the treatment group are more likely to own land or assets. Men in the control group are considerably more empowered than women, so that being in the KhetScore treatment group likely did not “move the needle” to a measurable degree among them. Overall, our results provide strong evidence for the effectiveness of the KhetScore loans in empowering women and improving intra-household gender relations.

Finally, in Table 9 we report the effect of the program on several women’s mental health outcomes, which are effectively measures of perceived stress, for both the female client (Panel A) and another female household member, who are likely co-signees on the loan, if the client was a male (Panel B). We asked women to rate on a Likert scale ranging from “never” (1) to “very often” (5) how often they felt “unable to control the important things in life”, “confident about ability to handle personal problems”, “confident that things were going their way”, and “difficulties were piling up so high that they could not overcome”. Then, the answers were recoded so that a higher score indicates a higher degree of stress, and a composite stress score was constructed by taking the average of the female respondent’s answers to the four questions. It is worth noting that, in general, other female family members of male clients report higher levels of stress on average (composite stress scores of 2.96 versus 1.3), suggesting more mental and emotional health

[8] The lack of an effect on whether farmers decided to cultivate during rabi 2021-2022 may be an artifact of the loan approval process. If farmers had not cultivated during rabi over three consecutive years, they would have been denied credit, regardless of their KhetScore or other qualifying factors.

[9] During both seasons, the program increased seeds purchases and hiring of female labour (the latter statistically significant only for kharif 2022, due to less precise estimates in the rabi season), which suggests that respondents are using some of their loans to hire labour, and free up time for themselves to allocate to other activities. At the same time, in both seasons, treatment farmers spent less on renting in additional land for cultivation, and only in the kharif season, on hiring machinery. There is also some evidence that households in the treatment group allocated less personal labour to agricultural production during kharif 2022. If we were to include the opportunity cost of the primary DER client’s labour in the cost of production, profits and returns on investments, then this reduction in one’s own labour supply would manifest itself in a significant decrease in the costs of production, a significant increase in the return of investment, and an even greater increase in profits during kharif.

problems among this subsample. We find that the program reduced stress levels, but only among the other female household members that were not directly targeted by DER, by 0.55 points in composite stress score (Panel B, column 1). Looking at each stress indicator, we also find that the program had beneficial impacts, though there is some variation in who (the female DER client versus another female household member of male DER clients) experienced this benefit. In particular, among female household members of male DER clients (Panel B), we find that the program decreased the frequency with which women felt control over important things in their life (column 2), increased the frequency of feeling confident in their ability to handle personal problems (column 3), and decreased the frequency with which women felt that difficulties were piling up so high that they could not overcome them (column 5). In terms of feeling control over the important things in life, the measured effect is around 10 percent of the average score among women in the control group. As for confidence in ability to handle personal problems, the effect is 13 percent of the average in the control group. In the case of feeling difficulties piling up, the effect is an even more pronounced 1.2-point reduction, which is greater than 40 percent of the average score among the control group, signifying a substantial reduction in women feeling overwhelmed. Among female DER clients (Panel A), we observe that the program increased the frequency of feeling confident in their ability to handle personal problems (column 3), and an increase in the frequency with which women felt that things were going their way (column 4).

In sum, the results from the program are highly encouraging. They suggest that the program has wide-ranging beneficial impacts for women, in terms of increasing access and utilization of credit, improving their ability to contribute to household decision-making, their control over income and assets, and reducing their overall levels of stress, thereby improving well-being. These latter two sets of results (those presented in Table 8 andTable 9) also highlight the value of interviewing multiple family members within beneficiary households. Had this research only focused on interviewing the household head or the client, it is very likely that we would have missed out on observing some interesting – and important – intrahousehold spillovers of this credit and insurance bundle.

### *4.4. Cost analysis*

To determine the costs of the intervention, we focused on the costs of implementing loans and insurance using KhetScore relative to conventional methods for providing financial services, but holding the distribution channel constant, since DER leverages existing lending and insurance operations of financial service providers. We distinguish between the fixed costs of the research and development around KhetScore, and the marginal costs of providing the digital credit and insurance products. The cost estimates are provided in Table 10.

The total one-off R&D costs associated with launching the KhetScore program are USD 76,000. The fixed cost of loan operations, including project management, staff travel, field office costs, app maintenance and communication material, are another approximately USD 20,000.

## 4. Conclusion

In this impact evaluation, we found that KhetScore loans have a wide range of significant and meaningful impacts that benefit participants in our study area. We find evidence of a significant increase in the uptake (62 percent higher than the control) and renewal (28 percent higher than the control) of agricultural insurance, and an overall increase in familiarity with the terms and conditions of crop insurance. The program also increased overall utilization of credit, especially among women. Much of this overall increase comes from an expansion in formal credit uptake (by about 23 percentage points on average, and by more than 34 percent among women) and not merely from a shift from informal to formal credit . In addition, households in the treatment group were more than 40 percentage points less likely to report facing difficulty in repaying their loans, indicating that the KhetScore loan and insurance bundle had particularly favorable terms.

Local average treatment effect estimates for the 2022 monsoon (kharif) season found that the treatment increased revenues and profits per acre by more than INR 7,500(USD 101) and INR 8,500(USD 114) respectively. During the 2021-2022 dry season (rabi), local average treatment effects suggest that treatment households increased their cultivated area by nearly 2 acres, whilst the total cost of production per acre fell by INR 10,000(USD 134) perhaps as treatment farmers generated economies of scale. As a result, treatment households had significantly higher agricultural profits, with kharif profits nearly doubling those in the control group, and rabi profits offsetting losses suffered by farmers in the control group.

We also observe important impacts on women's empowerment and mental health. Compared to female DER clients in the control group, those in the treatment group were 28 percentage points more likely to report making contributions to household decisions regarding borrowing and 25 percentage points more likely to make contributions to household decisions about how to use borrowed money. What's more, we find that the program had beneficial effects on women's empowerment that spilled over to other female household members who were not the direct recipients of the credit-insurance product. In particular, they were 38 percentage points more likely to report providing input into household livelihood decisions and to report having control over the use of income, and 35 percent more likely to have increased their reported asset ownership, despite not being the direct recipient of credit. We also find that the program had a beneficial effect on reducing stress levels, and while some of these effects were felt by DER clients, these effects were especially pronounced among the other female household members who co-signed the loans. These findings also underscore the value of surveying not only the (typically male) head of the household, but also other household members since the impacts of an intervention may differ across members of a household.

In this regard, it is worth noting that at baseline, women reported more often than men that the introduction of KhetScore loan bundled with insurance would make them more likely to apply for loans and that they would be interested in borrowing larger amounts. Indeed, over the course of this impact evaluation, we find beneficial impacts over a wide range of agricultural and gender parity outcomes. In particular, this impact evaluation highlights the potential of this innovative financial product in bringing about transformative changes in rural economies by enhancing financial literacy, expanding access to credit and insurance services, boosting agricultural investment and production, promoting women's empowerment, and alleviating some of the psychological stresses often associated with subsistence farming.

Our findings suggest that the KhetScore credit-scoring methodology, notably its ability to reduce transaction costs for both borrowers and lenders, serves to mitigate credit rationing while simultaneously broadening and enhancing the inclusivity of rural finance. In particular, KhetScore's elimination of paperwork prerequisites, specifically the need for land titles, extends access to formal credit to a previously underserved group of potential borrowers. Furthermore, the incorporation of crop insurance may alleviate collateral requirements, addressing both risk-related and quantity-related constraints in formal borrowing. These results provide valuable insights for policymakers interested in expanding access to credit and insurance for sharecroppers and tenant farmers who lack documented land rights.

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## Table 2. Summary statistics of DER clients in treatment and control villages

| | Full sample | | Control | | Treatment | | Difference (T-C) | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | N | Mean | N | Mean | Mean | Std. Dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A. Socio-demographic characteristics** | | | | | | | | |
| Female | 1709 | 0.693 | 839 | 0.733 | 870 | 0.654 | -0.079 | (0.116) |
| Age | 1708 | 42.306 | 839 | 42.286 | 869 | 42.326 | 0.040 | (1.115) |
| | | (8.717) | | (8.707) | | (8.732) | | |
| Can read and write | 1709 | 0.853 | 839 | 0.839 | 870 | 0.867 | 0.028 | (0.041) |
| Completed at least primary school | 1709 | 0.749 | 839 | 0.775 | 870 | 0.724 | -0.051 | (0.051) |
| Completed at least secondary school | 1709 | 0.253 | 839 | 0.253 | 870 | 0.254 | 0.001 | (0.047) |
| Caste/tribe | | | | | | | | |
| - General Caste | 1499 | 0.363 | 776 | 0.313 | 723 | 0.416 | 0.103** | (0.047) |
| - Scheduled Caste | 1499 | 0.360 | 776 | 0.428 | 723 | 0.288 | -0.140*** | (0.052) |
| - Scheduled Tribe | 1499 | 0.100 | 776 | 0.107 | 723 | 0.093 | -0.014 | (0.032) |
| - Other Backward Class | 1499 | 0.177 | 776 | 0.152 | 723 | 0.203 | 0.051 | (0.051) |
| Household income | | | | | | | | |
| - Low (below ₹ 90,000 per year) | 1709 | 0.534 | 839 | 0.520 | 870 | 0.548 | 0.029 | (0.084) |
| - Medium (₹ 90,000 - 120,000 p/year) | 1708 | 0.281 | 838 | 0.313 | 870 | 0.251 | -0.062 | (0.039) |
| - High (above ₹ 120,000 per year) | 1708 | 0.185 | 838 | 0.168 | 870 | 0.201 | 0.033 | (0.070) |
| **Panel B. Experience with credit and crop insurance** | | | | | | | | |
| Purchased on credit in past 12 months | 1708 | 0.489 | 838 | 0.415 | 870 | 0.561 | 0.146*** | (0.052) |
| Borrowed money in past 12 months | 1706 | 0.291 | 837 | 0.296 | 869 | 0.285 | -0.011 | (0.055) |
| Desired loan size for last season | 1704 | 37620 | 835 | 37157 | 869 | 38064 | 908 | (1860) |
| | | (15588) | | (15129) | | (16013) | | |
| Ever had crop insurance | 1499 | 0.0327 | 776 | 0.0271 | 723 | 0.0387 | 0.012 | (0.014) |
| Now having crop insurance | 1499 | 0.0147 | 776 | 0.0116 | 723 | 0.018 | 0.006 | (0.008) |
| Received pay-out from crop insurance | 1499 | 0.00934 | 776 | 0.00773 | 723 | 0.0111 | 0.003 | (0.006) |
| **Panel C. Agricultural outcomes** | | | | | | | | |
| Cultivated in last Kharif † | 1504 | 0.858 | 735 | 0.863 | 769 | 0.854 | -0.008 | (0.048) |
| Cultivated in last Rabi | 1681 | 0.745 | 820 | 0.820 | 861 | 0.675 | -0.145** | (0.072) |
| Total cultivated land (in acres) | 1365 | 2.050 | 714 | 2.011 | 651 | 2.093 | 0.082 | (0.175) |
| | | (1.176) | | (1.128) | | (1.227) | | |
| - Small farmer % (0-2.5 acres) | 1365 | 0.750 | 714 | 0.770 | 651 | 0.728 | -0.042 | (0.053) |
| - Marginal farmer % (2.5-5 acres) | 1365 | 0.229 | 714 | 0.211 | 651 | 0.247 | 0.036 | (0.048) |
| - Medium farmer % (5-10 acres) | 1365 | 0.021 | 714 | 0.018 | 651 | 0.025 | 0.006 | (0.010) |
| Cultivated paddy | 1365 | 0.994 | 714 | 0.996 | 651 | 0.992 | -0.003 | (0.004) |
| Cultivated lentil | 1365 | 0.027 | 714 | 0.006 | 651 | 0.051 | 0.045 | (0.029) |
| Crop was damaged | 1365 | 0.261 | 714 | 0.272 | 651 | 0.249 | -0.023 | (0.060) |
| Total revenue per acre for all crops | 1365 | 22950 | 714 | 21421 | 651 | 24628 | 3206 | (2239) |
| | | (14866) | | (13079) | | (16453) | | |
| Cost of production excl. own labor | 1365 | 13773 | 714 | 13806 | 651 | 13737 | -69.095 | (1275) |
| | | (6655) | | (5921) | | (7380) | | |
| Profit from all crops excl. own labor | 1365 | 9177 | 714 | 7615 | 651 | 10891 | 3275** | (1433) |
| | | (13617) | | (13034) | | (14040) | | |
| **Panel D. Credit rationing status** | | | | | | | | |
| Quantity rationed | 1706 | 0.511 | 837 | 0.478 | 869 | 0.543 | 0.065 | (0.047) |
| Risk rationed | 1706 | 0.291 | 837 | 0.283 | 869 | 0.299 | 0.016 | (0.042) |
| Credit unconstrained | 1706 | 0.198 | 837 | 0.239 | 869 | 0.158 | -0.081** | (0.035) |

*Notes:* Standard deviations are in parentheses. *Differences between Treatment and Control* are based on coefficient estimates derived from a regression in which we regress the variable of interest on a variable indicating treatment, with standard errors clustered by village (our unit of randomization). We test whether the coefficients on Treatment are different from zero and the *p*-values (not reported, though indicated by *, **, and *** symbols where applicable) are based on *t*-test statistics. †Variable was added to the survey form at a later stage and is therefore missing for the first set of respondents.

## Table 3. Number of participating farmers across implementation stages

| Season/ Crop | (1) KhetScore loan applied | (2) KhetScore loan received | (3) Enrolled Insurance | (4) Insurance payout made |
|---|---|---|---|---|
| Rabi 2020/21 (Paddy) | 90 | 62 (68.9%) | 95 | 7 |
| Kharif 2021 (Paddy) | 300 | 206 (68.7%) | 445 | 10 |
| Rabi 2021/22 (Paddy) | 350 | 319 (91.1%) | 319 | 0 |
| Kharif 2022 (Paddy) | 280 | 223 (79.6%) | 430 | 0 |

Note: Data reported only for the treatment arm (N=29 villages) since there was no intervention in the control villages.

## Table 4. Program effects on credit-related outcomes

| | Took up credit in past 12 months | | | Credit source: Formal | | | Credit source: Informal | | | Faced difficulty in repayment | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ITT | IV-LATE | BP-LATE | ITT | IV-LATE | BP-LATE | ITT | IV-LATE | BP-LATE | ITT | IV-LATE | BP-LATE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **Panel A.** | | | | | | | | | | | | |
| Treatment | 0.023 | 0.095 | 0.132 | 0.213*** | 0.883*** | 0.515** | -0.200*** | -0.828*** | -0.117** | -0.559*** | -1.066*** | -0.204** |
| Std. Err. or 95% CI | (0.035) | (0.144) | [-0.053, 0.326] | (0.032) | (0.130) | [0.436,0.551] | (0.027) | (0.136) | [-0.162, -0.0001] | (0.054) | (0.120) | [-0.254, -0.115] |
| **Panel B. Gender** | | | | | | | | | | | | |
| Total effect \| Male | -0.079 | -0.343 | 0.067 | 0.167*** | 0.752*** | 0.514** | -0.263*** | -1.166*** | -0.028** | -0.495*** | -0.979*** | -0.229** |
| Std. Err. or 95% CI | (0.050) | (0.237) | [-0.113, 0.337] | (0.046) | (0.175) | [0.432, 0.562] | (0.042) | (0.228) | [-0.151, -0.00002] | (0.069) | (0.127) | [-0.300, -0.0001] |
| Total effect \| Female | 0.157*** | 0.569*** | 0.305 | 0.259*** | 0.997*** | 0.424** | -0.102** | -0.432*** | -0.226** | -0.595*** | -1.082*** | -0.193** |
| Std. Err. or 95% CI | (0.045) | (0.160) | [-0.077, 0.498] | (0.043) | (0.150) | [0.042, 0.540] | (0.034) | (0.143) | [-0.305, -0.0001] | (0.089) | (0.196) | [-0.271, -0.00001] |
| **Panel C. Rationing status** | | | | | | | | | | | | |
| Total effect \| Unconstrained | 0.064 | 0.389 | 0.394 | 0.242*** | 1.666*** | 0.455 | -0.178*** | -1.280*** | -0.0002** | -0.653*** | -1.957*** | -0.00002 |
| Std. Err. or 95% CI | (0.053) | (0.336) | [-0.130, 1.000] | (0.054) | (0.459) | [-0.0001, 1.000] | (0.033) | (0.376) | [-0.147, -0.00001] | (0.075) | (0.480) | [-0.253, 0.0000009] |
| Total effect \| Quantity rationed | 0.025 | 0.081 | 0.209 | 0.204*** | 0.842*** | 0.535** | -0.183*** | -0.777*** | -0.0001** | -0.520*** | -1.002*** | -0.192** |
| Std. Err. or 95% CI | (0.042) | (0.171) | [-0.044, 0.442] | (0.033) | (0.131) | [0.448, 0.594] | (0.033) | (0.153) | [-0.111, -0.00004] | (0.068) | (0.104) | [-0.240, -0.00002] |
| Total effect \| Risk rationed | 0.032 | 0.087 | 0.065 | 0.215*** | 0.772*** | 0.488 | -0.207*** | -0.770*** | -0.158** | -0.496*** | -0.942*** | -0.038** |
| Std. Err. or 95% CI | (0.043) | (0.152) | [-0.096, 0.537] | (0.054) | (0.171) | [-0.003, 0.611] | (0.047) | (0.162) | [-0.238, -0.00005] | (0.090) | (0.190) | [-0.210, -0.00001] |
| Observations | | 1,621 | | | 1,621 | | | 1,621 | | | 632 | |
| Control group mean | | 0.353 | | | 0.140 | | | 0.223 | | | 0.756 | |

*Notes:* Standard errors in parentheses clustered by village, and 95 percent confidence intervals generated from nonparametric bootstrap in brackets. *** p < 0.01, ** p < 0.05, * p < 0.10. All dependent variables are binary. Data on whether the client faced difficulty in repaying loans is only available among respondents who indicated that they had taken out a loan. All regressions control for block fixed effects and baseline values for credit uptake (binary) and agricultural profits per acre excluding the cost of own labor, as well as additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary). In Panels B and C, rows labeled "Total effect…" in ITT and IV-LATE columns correspond to linear combinations of regression coefficients (where applicable), including the regression coefficient associated with random assignment ($T_{ib}$) and the corresponding interaction terms from equations (2) and (3), respectively. Rows labeled "Total effect…" in BP-LATE columns reflect LATE estimates based on sub-sample recursive bivariate probit regressions.

## Table 5. Program effects on insurance take-up, renewal, and knowledge

| | Took up insurance | | | Renewed insurance | | | Insurance knowledge | |
|---|---|---|---|---|---|---|---|---|
| | ITT | IV-LATE | BP-LATE | ITT | IV-LATE | BP-LATE | ITT | IV-LATE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A.** | | | | | | | | |
| Treatment | 0.617*** | 2.547*** | 0.230** | 0.282*** | 1.008*** | 0.256** | 0.493*** | 1.596*** |
| Std. Err. or 95% CI | (0.044) | (0.352) | [0.164, 0.279] | (0.068) | (0.249) | [0.062, 0.325] | (0.153) | (0.396) |
| **Panel B. Gender** | | | | | | | | |
| Total effect \| Male | 0.630*** | 2.818*** | 0.251** | 0.073 | 0.256 | 0.188 | 0.517*** | 1.337*** |
| Std. Err. or 95% CI | (0.046) | (0.545) | [0.144, 0.322] | (0.079) | (0.339) | [-0.065, 0.335] | (0.117) | (0.276) |
| Total effect \| Female | 0.601*** | 2.364*** | 0.226** | 0.570*** | 2.020*** | 0.320 | 0.453 | 1.259 |
| Std. Err. or 95% CI | (0.069) | (0.360) | [0.135, 0.283] | (0.063) | (0.313) | [-0.884, 0.347] | (0.356) | (1.022) |
| **Panel C. Rationing status** | | | | | | | | |
| Total effect \| Unconstrained | 0.658*** | 4.473*** | 0.344** | 0.333*** | 2.043*** | 0.225 | 0.516** | 2.048** |
| Std. Err. or 95% CI | (0.057) | (1.081) | [0.00001, 0.433] | (0.101) | (0.746) | [-1.000, 0.380] | (0.246) | (0.931) |
| Total effect \| Quantity rationed | 0.639*** | 2.586*** | 0.190** | 0.285*** | 1.044*** | 0.260** | 0.527*** | 1.345*** |
| Std. Err. or 95% CI | (0.051) | (0.431) | [0.099, 0.235] | (0.070) | (0.279) | [0.001, 0.351] | (0.143) | (0.335) |
| Total effect \| Risk rationed | 0.590*** | 2.078*** | 0.172** | 0.189* | 0.576* | 0.193 | 0.703** | 1.716** |
| Std. Err. or 95% CI | (0.050) | (0.312) | [0.00006, 0.224] | (0.114) | (0.345) | | (0.322) | (0.757) |
| Observations | | 1,621 | | | 950 | | 687 | |
| Control group mean | | 0.280 | | | 0.394 | | 3.047 | |

*Notes*: Standard errors in parentheses clustered by village, and 95 percent confidence intervals generated from nonparametric bootstrap in brackets. *** $p$ < 0.01, ** $p$ < 0.05, * $p$ < 0.10. The first two dependent variables are binary. The third, "Insurance knowledge score", is the number of correct answers to six True/False statements about crop insurance, and consequently takes integer values 0-6. All regressions control for block fixed effects and baseline values for insurance uptake (binary) and agricultural profits per acre excluding the cost of own labor, as well as additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary). We do not have baseline data on insurance renewals or the client's familiarity with terms and conditions of crop insurance ("knowledge score"), so baseline insurance uptake proxies for these baseline values in regressions for which these outcomes are the dependent variable. In Panels B and C, rows labeled "Total effect…"in ITT and IV-LATE columns correspond to linear combinations of regression coefficients (where applicable), including the regression coefficient associated with $T_{ib}$ and the corresponding interaction terms from equations (2) and (3), respectively. Rows labeled "Total effect…" in BP-LATE columns reflect LATE estimates based on sub-sample recursive bivariate probit regressions.

## Table 6. Program effects on agricultural outcomes in the kharif (monsoon) season

| | Area cultivated | | Revenue per acre (in 10,000 INR) | | Cost per acre (in 10,000 INR) | | Profit per acre (in 10,000 INR) | |
|---|---|---|---|---|---|---|---|---|
| | ITT | IV-LATE | ITT | IV-LATE | ITT | IV-LATE | ITT | IV-LATE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (9) | (10) |
| **Panel A.** | | | | | | | | |
| Treatment | -0.003 | -0.012 | 0.189*** | 0.739*** | -0.024 | -0.091 | 0.228*** | 0.890*** |
| | (0.064) | (0.252) | (0.065) | (0.253) | (0.070) | (0.271) | (0.068) | (0.270) |
| **Panel B. Gender** | | | | | | | | |
| Total effect \| Male | 0.047 | 0.189 | 0.240*** | 0.988*** | 0.012 | 0.044 | 0.221** | 0.912** |
| | (0.086) | (0.339) | (0.076) | (0.265) | (0.115) | (0.463) | (0.109) | (0.438) |
| Total effect \| Female | -0.058 | -0.198 | 0.145 | 0.568 | -0.057 | 0.202 | 0.245*** | 0.916*** |
| | (0.098) | (0.358) | (0.095) | (0.361) | (0.056) | (0.205) | (0.061) | (0.246) |
| **Panel C. Rationing status** | | | | | | | | |
| Total effect \| Unconstrained | -0.015 | -0.110 | 0.207* | 1.365* | -0.116 | -0.709 | 0.267*** | 1.757*** |
| | (0.101) | (0.635) | (0.114) | (0.786) | (0.084) | (0.532) | (0.089) | (0.668) |
| Total effect \| Quantity rationed | -0.063 | -0.230 | 0.220*** | 0.816*** | 0.009 | 0.028 | 0.239* | 0.890** |
| | (0.097) | (0.367) | (0.077) | (0.275) | (0.131) | (0.469) | (0.122) | (0.437) |
| Total effect \| Risk rationed | 0.048 | 0.144 | 0.122 | 0.417 | -0.056 | -0.180 | 0.222*** | 0.728*** |
| | (0.082) | (0.261) | (0.103) | (0.320) | (0.067) | (0.223) | (0.072) | (0.223) |
| Observations | 1,468 | | 1,468 | | 1,468 | | 1,468 | |
| Control group mean | 2.076 | | 1.248 | | 1.131 | | 0.125 | |

*Notes*: Standard errors in parentheses clustered by village. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Cost per acre, return on investment, and profit per acre all estimated *excluding* own labor. All regressions control for block fixed effects and baseline values for credit uptake (binary) and agricultural profits per acre excluding the cost of own labor, as well as additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary). Rows labeled "Total effect…" in Panels B and C correspond to linear combinations of regression coefficients (where applicable), including the regression coefficient associated with $T_{ib}$ and the corresponding interaction terms from equations (2) and (3), respectively.

## Table 7. Program effects on agricultural outcomes in the rabi (winter) season

| | Cultivated in Rabi | | | Area cultivated | | Revenue per acre (in 10,000 INR) | | Cost per acre (in 10,000 INR) | | Profit per acre (in 10,000 INR) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (12) | (13) |
| | ITT | IV-LATE | BP-LATE | ITT | IV-LATE | ITT | IV-LATE | ITT | IV-LATE | ITT | IV-LATE |
| **Panel A.** | | | | | | | | | | | |
| Treatment | -0.009 | -0.037 | 0.252** | 0.522*** | 1.731*** | 0.064 | 0.210 | -0.323*** | -1.056*** | 1.426*** | 4.697*** |
| Std. Err. or 95% CI | (0.037) | (0.153) | [0.091, 0.345] | (0.086) | (0.284) | (0.107) | (0.359) | (0.061) | (0.219) | (0.225) | (0.813) |
| **Panel B. Gender** | | | | | | | | | | | |
| Treatment \| Male | -0.022 | -0.096 | 0.231** | 0.403*** | 1.484*** | -0.011 | -0.023 | -0.249*** | -0.925*** | 1.427*** | 5.115*** |
| Std. Err. or 95% CI | (0.042) | (0.184) | [0.001, 0.360] | (0.114) | (0.437) | (0.120) | (0.430) | (0.065) | (0.247) | (0.250) | (1.078) |
| Total effect \| Female | 0.023 | 0.081 | 0.291** | 0.618*** | 1.889*** | 0.129 | 0.349 | -0.509*** | -1.496*** | 1.212*** | 3.952*** |
| Std. Err. or 95% CI | (0.063) | (0.237) | [0.017, 0.381] | (0.139) | (0.393) | (0.155) | (0.456) | (0.111) | (0.345) | (0.408) | (1.210) |
| **Panel C. Rationing status** | | | | | | | | | | | |
| Treatment \| Unconstrained | 0.036 | 0.220 | 0.272** | 0.115 | 1.100 | 0.222 | 1.105 | -0.327** | -1.857** | 1.020** | 6.428** |
| Std. Err. or 95% CI | (0.063) | (0.424) | [0.00001, 0.386] | (0.133) | (0.717) | (0.146) | (0.800) | (0.131) | (0.803) | (0.405) | (2.619) |
| Total effect \| Quantity rationed | -0.009 | -0.040 | 0.2986** | 0.665*** | 1.947*** | 0.044 | 0.137 | -0.330*** | -0.956*** | 1.712*** | 4.944*** |
| Std. Err. or 95% CI | (0.046) | (0.182) | [0.075, 0.407] | (0.131) | (0.413) | (0.153) | (0.443) | (0.085) | (0.263) | (0.400) | (1.194) |
| Total effect \| Risk rationed | -0.066 | -0.220 | -0.185 | 0.567*** | 1.729*** | 0.070 | 0.215 | -0.352*** | -1.051*** | 1.356*** | 4.134*** |
| Std. Err. or 95% CI | (0.053) | (0.166) | | (0.110) | (0.338) | (0.137) | (0.395) | (0.081) | (0.245) | (0.211) | (0.693) |
| Observations | | 1,527 | | 939 | | 939 | | 939 | | 939 | |
| Control group mean | | 0.710 | | 1.692 | | 1.219 | | 1.530 | | -1.905 | |

*Notes*: Standard errors in parentheses clustered by village, and 95 percent confidence intervals generated from nonparametric bootstrap in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions control for block fixed effects and baseline values for credit uptake (binary) and agricultural profits per acre excluding the cost of own labor, as well as additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary). In Panels B and C, rows labeled "Total effect…" in IV-LATE columns correspond to linear combinations of regression coefficients (where applicable). Rows labeled "Total effect…" in BP-LATE columns correspond to local average treatment effect based on recursive bivariate probit estimates for corresponding sub-samples.

## Table 8. Program effects on contributions to household decision-making

| | Borrow decision (1) | Use of borrowed funds (2) | Input in livelihoods (3) | Control use of income (4) | Asset ownership (5) |
|---|---|---|---|---|---|
| **Panel A. Client** | | | | | |
| Treatment \| Male | 0.017 | 0.008 | -0.029 | 0.055 | 0.045** |
| | (0.039) | (0.042) | (0.049) | (0.053) | (0.017) |
| Treatment \| Female | 0.278*** | 0.252*** | 0.057 | 0.072 | 0.023 |
| | (0.054) | (0.062) | (0.050) | (0.048) | (0.038) |
| $R^2$ | 0.320 | 0.331 | 0.092 | 0.088 | 0.032 |
| Observations | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 |
| Control group mean | 0.427 | 0.450 | 0.803 | 0.716 | 0.893 |
| **Panel B. Other family member** | | | | | |
| Treatment \| Male | -0.067 | -0.028 | -0.060 | -0.004 | 0.021 |
| | (0.058) | (0.057) | (0.056) | (0.058) | (0.028) |
| Treatment \| Female | 0.028 | -0.004 | 0.379*** | 0.377*** | 0.351*** |
| | (0.032) | (0.022) | (0.051) | (0.053) | (0.038) |
| $R^2$ | 0.463 | 0.507 | 0.177 | 0.151 | 0.253 |
| Observations | 1,294 | 1,294 | 1,294 | 1,294 | 1,294 |
| Control group mean | 0.373 | 0.368 | 0.562 | 0.525 | 0.744 |

*Notes*: Standard errors in parentheses clustered by village. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions control for block fixed effects and baseline values for insurance uptake (binary), agricultural profits per acre excluding the cost of own labor, the baseline values for the outcome variable being evaluated, and additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary). Rows labeled "Total effect…" in correspond to linear combinations of regression coefficients (where applicable), including the regression coefficient associated with $T_{ib}$ and the corresponding interaction terms from equations (2) and (3), respectively.

## Table 9. Program effects on mental and emotional stress

| | Composite stress score | Unable to control important things | Confidence in ability to handle personal problems | Felt that things were going her way | Felt that difficulties were piling up |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Client** | | | | | |
| Treatment | 0.050 | 0.269 | 0.369* | 0.286* | 0.220 |
| | (0.065) | (0.171) | (0.192) | (0.170) | (0.161) |
| $R^2$ | 0.767 | 0.302 | 0.326 | 0.326 | 0.279 |
| Observations | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 |
| Control group mean | 1.275 | 1.408 | 1.780 | 1.648 | 1.309 |
| **Panel B. Other family member** | | | | | |
| Treatment | -0.550*** | -0.291*** | 0.508*** | 0.172 | -1.165*** |
| | (0.075) | (0.087) | (0.123) | (0.129) | (0.137) |
| $R^2$ | 0.241 | 0.167 | 0.149 | 0.138 | 0.259 |
| Observations | 740 | 740 | 740 | 740 | 740 |
| Control group mean | 2.963 | 3.381 | 3.639 | 3.249 | 3.361 |

*Notes*: Standard errors in parentheses clustered by village. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions control for block fixed effects and baseline values for insurance uptake (binary), agricultural profits per acre excluding the cost of own labor, the baseline values for the outcome variable being evaluated, and additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary). Rows labeled "Total effect…" in correspond to linear combinations of regression coefficients (where applicable), including the regression coefficient associated with $T_{ib}$ and the corresponding interaction terms from equations (2) and (3), respectively.

**Table 10. Implementation costs**

| | Cost per unit | Number of units | Total cost | |
|---|---|---|---|---|
| | | | INR | USD |
| **Research & Development (one-off cost)** | | | | |
| Personnel | | | 1,463,060 | 19,665 |
| Office/facilities | | | 690,000 | 9,274 |
| IT services | | | 243,994 | 3,279 |
| Data collection/licensing | | | 1,670,086 | 22,447 |
| Guarantee fund for initial de-risking of KhetScore | 10% per INR 34,000 loan | 450 farmers | 1,530,000 | 20,564 |
| ***Total one-off R&D cost*** | | | ***5,666,890*** | ***76,176*** |
| **Fixed cost per season** | | | | |
| Project management | | | 367,481 | 4,939 |
| Staff travel | | | 36,627 | 492 |
| Field office costs | | | 690,000 | 9,274 |
| App/portal maintenance | | | 248,400 | 3,339 |
| Communication material | | | 68,626 | 922 |
| ***Total fixed cost per season*** | | | ***1,411,135*** | ***18,966*** |
| **Variable cost per farmer** | | | | |
| Interest | 14% of loan | 34,000 | 4,760 | 64 |
| Insurance | 2% of loan | 34,000 | 680 | 9 |
| KhetScore reports | n/a | n/a | n/a | n/a |
| DER field staff | n/a | n/a | 374 | 5 |
| Staff transport, allowance | n/a | n/a | 37 | 0.5 |
| Printing, stationeries | n/a | n/a | 12 | 0.2 |
| ***Total cost per farmer*** | | | ***5,863*** | ***78.80*** |

***USD = INR 74.40***


**Figure 3. Map of Odisha, with study locations in Jajpur district**

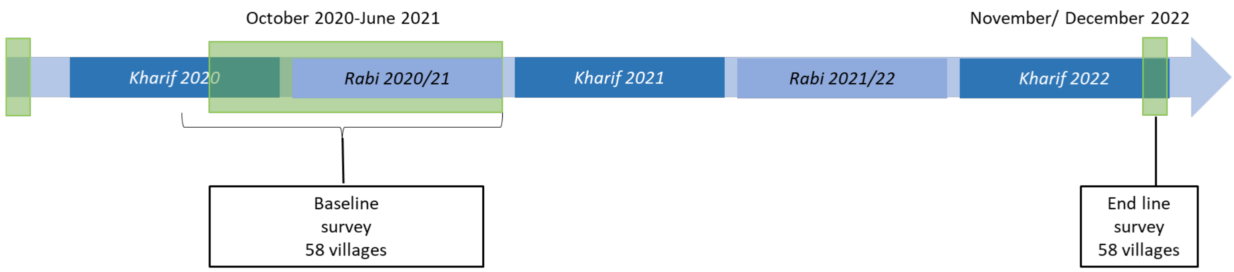
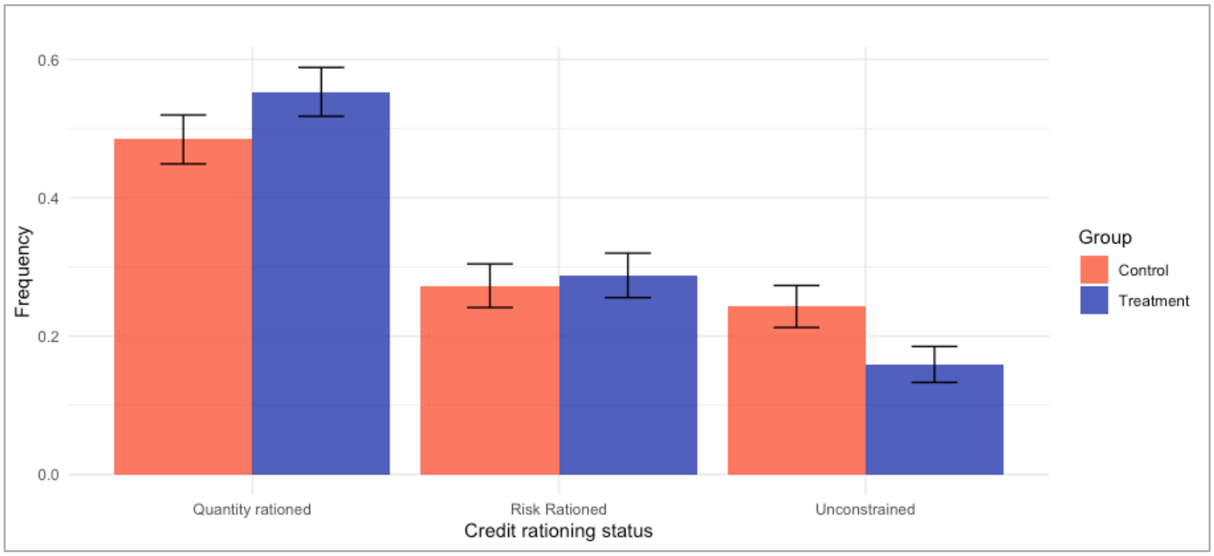



**Figure 2. Study timeline**




**Credit rationing status among DER's clients at baseline**

## Appendix A. Estimation of the recursive bivariate probit model

The recursive bivariate probit model takes the form:

$$D_i^* = \eta_T + \alpha T_i + \sum_{j=1}^{J} \theta_{jD} \mathbf{x}_{ijbD,0} + \varepsilon_{ibD}, \quad D_i = \mathbf{1}(D_i^* > 0),$$

$$Y_i^* = \eta_Y + \gamma D_i + \sum_{j=1}^{J} \theta_{jY} \mathbf{x}_{ijbY,0} + \varepsilon_{ibY}, \quad Y_i = \mathbf{1}(Y_i^* > 0), \tag{4}$$

$$\begin{pmatrix} \varepsilon_D \\ \varepsilon_Y \end{pmatrix} \mid \boldsymbol{X}_D, \boldsymbol{X}_Y \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$$

This model is a simultaneous equations model in which both equations (i.e., those for $D_i$ and $Y_i$) are binary dependent variable equations, and the disturbance terms in the two equations are jointly distributed according to a bivariate normal distribution with zero conditional means and correlation coefficient $\rho$. Greene (2018) notes that the endogenous nature of $D_i$ on the right-hand side of the second equation does not require any special consideration in formulating the log-likelihood function. Although it is not required that the vectors of covariates $\mathbf{x}_D$ and $\mathbf{x}_Y$ be the same, the inclusion of identical controls is permitted, and the omission of instrument $T_i$ from the second equation provides an exclusion restriction that aids in identification.[10] As with univariate probit regression models, coefficient estimates from equation are not directly interpretable as marginal effects or as LATEs. Chiburis et al. (2011) provide an expression for the LATE from a recursive bivariate probit:

$$\Delta_{LATE} = \frac{[\Phi_2(\eta_T + \alpha, \eta_Y + \gamma, \rho) + \Phi_2(-(\eta_T + \alpha), \eta_Y, -\rho)] - [\Phi_2(\eta_T, \eta_Y + \gamma, \rho) + \Phi_2(-\eta_T, \eta_Y, -\rho)]}{\Phi(\alpha) - \Phi(0)} \tag{5}$$

where $\Phi_2$ and $\Phi$ indicate, respectively, the bivariate and univariate normal cumulative distribution functions.

[10] Importantly, Han and Lee (2019) have demonstrated that in a bivariate probit model with common exogenous covariates and no excluded instruments, the structural parameters are not identified.

## Table A1. Agricultural expenditures (INR) – kharif (monsoon) season

| | Seed | Fertilizer | Irrigation | Machinery | Rent | Male labor | Female labor | Family labor - own | Family labor - other male | Family labor - other female |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Panel A - Full sample** | | | | | | | | | | |
| Treatment | 1,065.02*** | -1,895.70 | -709.44 | -2,297.87 | -2,173.38*** | -227.29 | 3,810.03*** | -33.82** | 6.47 | -5.88 |
| Std Error | (307.39) | (1,840.49) | (652.87) | (1,529.44) | (627.48) | (1,688.42) | (638.18) | (13.13) | (6.99) | (8.503) |
| **Panel B - By gender** | | | | | | | | | | |
| Treatment \| Male | 2,414.27*** | -344.31 | -155.13 | -295.30 | -1,712.80* | 150.97 | 6,388.96*** | -60.95*** | 7.226 | -7.142 |
| Std. Error | (501.61) | (2,450.63) | (980.29) | (2,212.05) | (645.54) | (2,401.42) | (988.74) | (15.30) | (9.26) | (12.05) |
| Total effect \| Female | 162.99 | -3,688.26** | -515.25 | -6,378.81*** | -3,655.29*** | -123.98 | 1,602.89* | 29.93** | 2.72 | 15.74** |
| Std. Error | (496.17) | (1,733.16) | (590.54) | (2,197.62) | (1,151.28) | (2,397.81) | (890.12) | (13.56) | (9.39) | (7.90) |
| **Panel C – By credit rationing status** | | | | | | | | | | |
| Treatment \| Unconstrained | 845.81 | -2,066.79 | 21.99 | -5,857.18* | -3,550.38** | -2,898.30 | 5,284.68*** | -36.59 | 5.82 | 2.57 |
| Std. Error | (1,016.67) | (2,600.39) | (826.54) | (2,999.99) | 1,684.99) | (3,644.85) | (1,756.59) | (23.67) | (16.75) | (15.29) |
| Total effect \| Quantity rationed | 1,406.78*** | -3,814.82 | -1,415.80 | -2,419.69 | -2,163.69*** | -712.63 | 3,751.25*** | -40.76*** | 6.27 | -6.59 |
| Std. Error | (470.31) | (3,431.10) | (1,229.22) | (2,065.04) | (704.79) | (2,450.28) | (748.62) | (15.69) | (8.78) | (10.61) |
| Total effect \| Risk rationed | 91.85 | 718.44 | 254.00 | -447.80 | -1,147.01** | -1,143.22 | 2,831.98*** | -35.14** | 13.72* | -13.12 |
| Std. Error | (449.99) | (1,226.13) | (462.12) | (1,737.55) | (567.91) | (1,729.61) | (1,105.07) | (15.59) | (8.21) | (10.19) |
| Number of observations | 982 | 982 | 982 | 982 | 982 | 982 | 982 | 982 | 982 | 982 |
| Mean control group | 2,463.01 | 5,490.02 | 1,715.78 | 4,781.68 | 1,143.23 | 5,875.66 | 1,013.23 | 40.57 | 25.94 | 17.40 |

*Notes*: Standard errors in parentheses clustered by village. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions control for block fixed effects and baseline values for insurance uptake (binary), agricultural profits per acre excluding the cost of own labor, the baseline values for the outcome variable being evaluated, and additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary).

## Table A2. Agricultural expenditures (INR) – rabi (dry) season

| | Seed | Fertilizer | Irrigation | Machinery | Rent | Male labor | Female labor | Family labor - own | Family labor - other male | Family labor - other female |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Panel A - Full sample** | | | | | | | | | | |
| Treatment | 0.051** | -0.075* | -0.017 | 0.582 | -0.179* | 0.592 | 0.116 | 3.935 | -2.760 | -1.817 |
| | (0.020) | (0.039) | (0.019) | (0.549) | (0.106) | (0.567) | (0.221) | (3.261) | (2.292) | (1.770) |
| R-squared | 0.033 | 0.166 | 0.068 | 0.178 | 0.058 | 0.116 | 0.058 | 0.072 | 0.042 | 0.103 |
| **Panel B - By gender** | | | | | | | | | | |
| Treatment | 0.074*** | 0.084 | -0.043* | 1.218* | -0.266* | -0.722 | -0.106 | -1.854 | -8.253*** | -5.420** |
| | (0.027) | (0.054) | (0.022) | (0.673) | (0.139) | (0.639) | (0.278) | (3.692) | (2.939) | (2.316) |
| Female | 0.022 | 0.501*** | -0.079*** | 3.888*** | -0.349** | -2.032*** | -0.104 | -17.132*** | -3.764 | -7.035*** |
| | (0.030) | (0.077) | (0.023) | (0.749) | (0.149) | (0.660) | (0.207) | (3.881) | (3.485) | (1.636) |
| Treatment x Female | -0.062 | -0.424*** | 0.071** | -1.696* | 0.233 | 3.498*** | 0.590* | 15.418*** | 14.631*** | 9.597*** |
| | (0.041) | (0.092) | (0.031) | (1.002) | (0.182) | (0.911) | (0.333) | (4.828) | (4.437) | (2.505) |
| R-squared | 0.038 | 0.200 | 0.077 | 0.184 | 0.061 | 0.142 | 0.062 | 0.088 | 0.068 | 0.127 |
| Number of observations | 992 | 992 | 992 | 992 | 992 | 992 | 992 | 992 | 992 | 992 |
| Mean control group | 0.275 | 0.540 | 0.163 | 4.530 | 0.569 | 7.126 | 1.275 | 41.090 | 16.655 | 7.737 |

*Notes*: Standard errors in parentheses clustered by village. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressions control for block fixed effects and baseline values for insurance uptake (binary), agricultural profits per acre excluding the cost of own labor, the baseline values for the outcome variable being evaluated, and additional control variables including age (categorical), literacy (binary), caste (binary), a binary indicator for whether Dvara E-Registry had ongoing operations in the client's village at the time of baseline (as opposed to initiating new operations as part of this project), and an indicator for whether the client had cultivated during the preceding Rabi season (binary).