Impacts of an innovative credit-insurance bundle for smallholder farmers:

Evidence from a cluster randomized trial in Odisha, India

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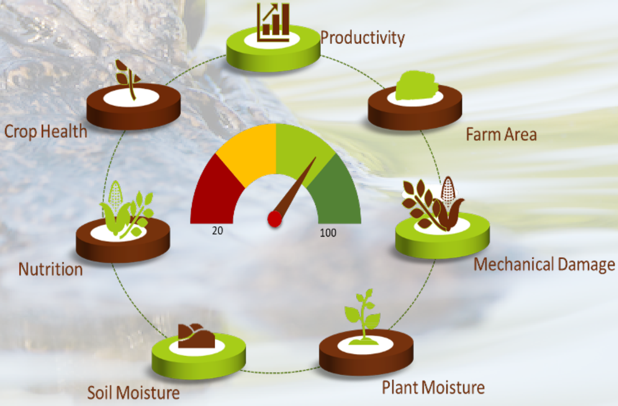
- **What if we can overcome information asymmetries at a low cost, using innovative technologies?**
  - Credit-scoring + monitoring using satellite imagery and crop analytics (KhetScore)
  - Picture-based insurance (PBI) (Ceballos, Kramer, and Robles, 2019)

KhetScore: Agricultural credit bundled with insurance



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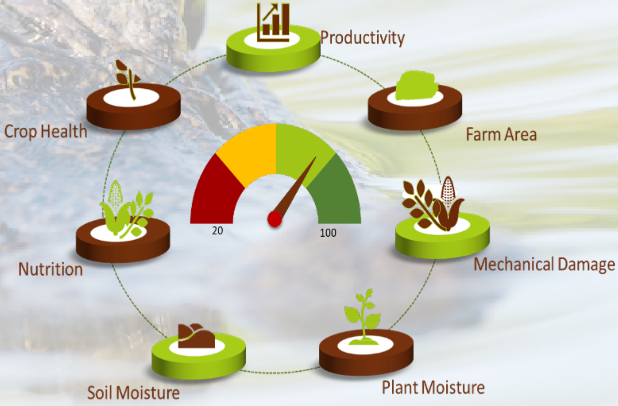

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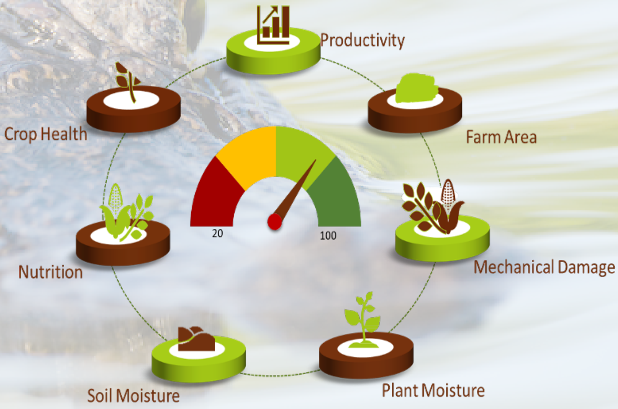

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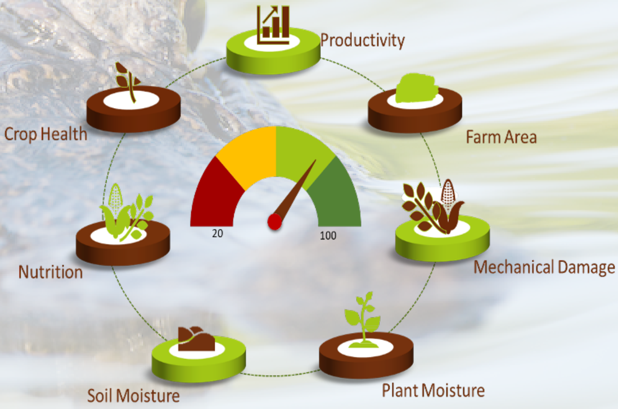

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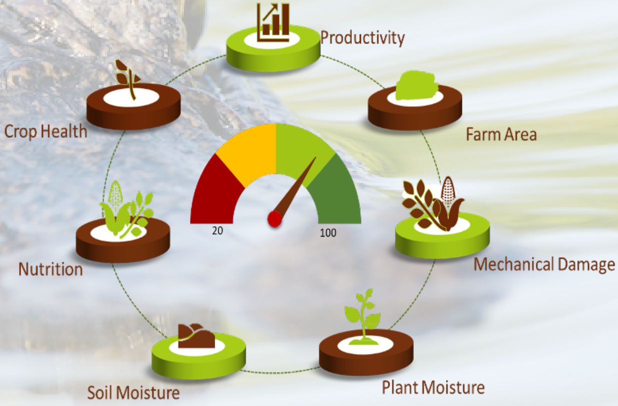

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- How do these impacts vary depending on whether a client is/was risk or quantity rationed?
  ▸ Heterogeneity by credit rationing

Study context

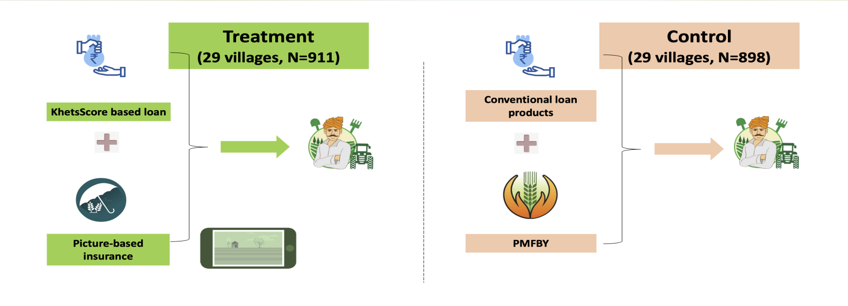
Odisha, India

- One of the largest producers of food grain in India, particularly paddy (around 55% of the area under cultivation used for food grain production)
- Two seasons per year: the summer monsoon (Kharif) season, with farmers mainly producing paddy, and winter (Rabi) season, during which many farmers do not cultivate.
- Increasing investments in high-value crops during Rabi season may be one way to transform agricultural livelihoods in the state.

Jajpur district: low-lying coastal plain

- Main risks during Kharif season: Floods and cyclones
- Limited investments during Rabi season – even when irrigation is available – due to a lack of credit and risk.
- Sharecropping and marginalization of tenant famers limits access to government-subsidized credit and insurance
- Study implemented in two blocks: Dashrathpur and Jajpur

Study design: cluster randomized trial



Evaluation outcomes

Outcomes of interest	Outcome indicators
Credit and insurance market development	Credit uptake (total, formal, informal), difficulties in repayment of loan; insurance uptake and renewal, awareness of insurance concepts ▸ Details
Agricultural outcomes	Area cultivated under paddy rice, revenue per acre, costs per acre, profit per acre, return on (agricultural) investment
Gender parity	Contributions to household borrowing decisions and decisions about how to use borrowed funds; women's empowerment (Pro-WEAI)
Well-being	Mental health (stress)

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Baseline characteristics of primary clients

	Control			Treatment			
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total cultivated land (acres)	716	2.01	1.13	651	2.09	1.23	0.64
- Small farmer (0-2.5 acres)	716	0.77	0.42	651	0.73	0.45	0.43
- Marginal farmer (2.5-5 acres)	716	0.21	0.41	651	0.25	0.43	0.47
Medium farmer 5-10 acres	716	0.02	0.13	651	0.03	0.16	0.53
Cultivated paddy (=1)	716	1.00	0.07	651	0.99	0.09	0.42
Cultivated lentil (=1)	716	0.01	0.08	651	0.05	0.22	0.13
Cultivated vegetables (=1)	716	0.01	0.08	651	0.03	0.16	0.31
Crop was damaged (=1)	716	0.27	0.45	651	0.25	0.43	0.70
Ever had crop insurance (=1)	798	0.03	0.16	722	0.04	0.19	0.37
Now having crop insurance (=1)	798	0.01	0.11	722	0.02	0.13	0.38
Received pay-out from crop insurance (=1)	798	0.01	0.09	722	0.01	0.11	0.53
Women's Dietary Diversity (MDD-W)	798	3.97	1.50	722	3.93	1.56	0.81
Household Dietary Diversity (HDDS)	798	7.58	1.31	722	7.56	1.41	0.90
Food Consumption Score (FCS)	798	81.09	24.55	722	81.22	27.11	0.98
Stress indicator	350	3.45	0.36	250	3.35	0.42	0.14
Total revenue per acre for all crops (INR)	716	21,387	13,069	651	24,628	16,453	0.15
Cost of production excl. own labour (INR)	716	13,783	5,916	651	13,737	7,380	0.97
Profit from all crops excl. own labour	716	7,604	13,023	651	10,891	14,040	0.03

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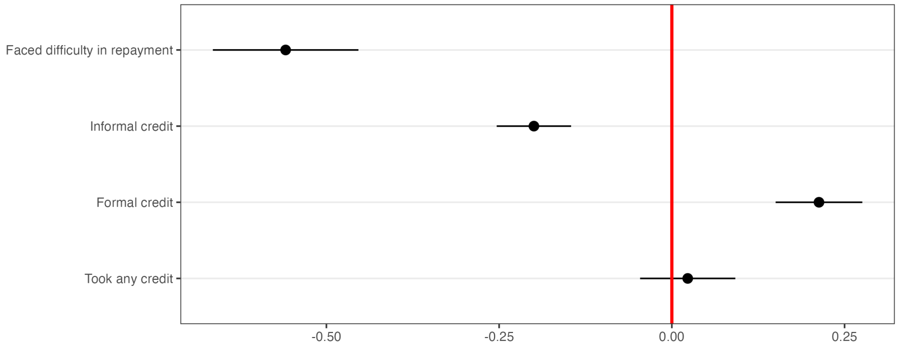
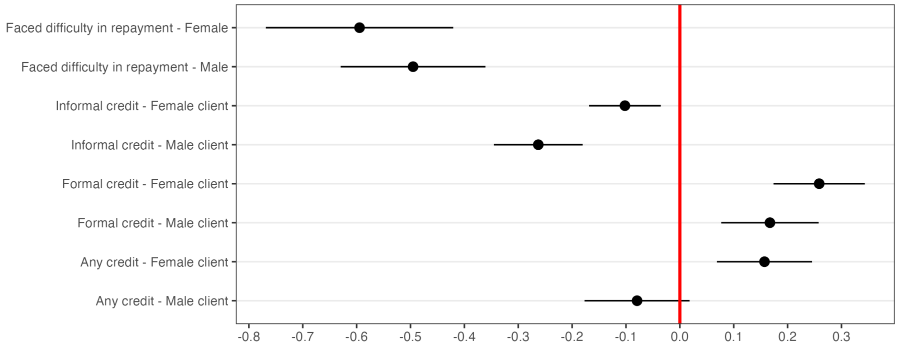
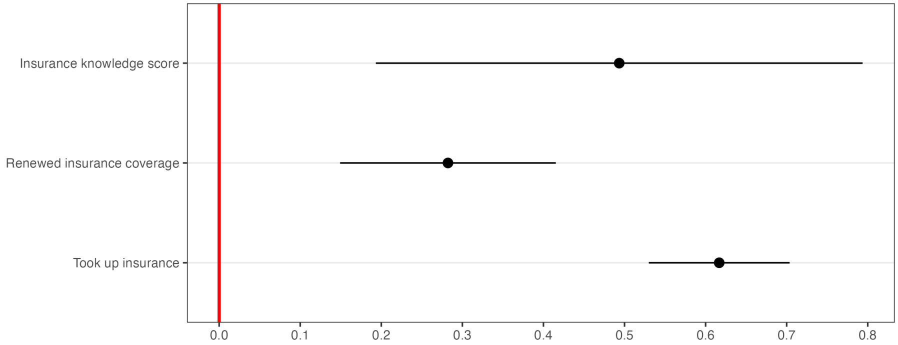


Treatment effects (ITT) on credit uptake by gender of client



Treatment effects (ITT) on insurance take-up, renewal, and familiarity with insurance concepts



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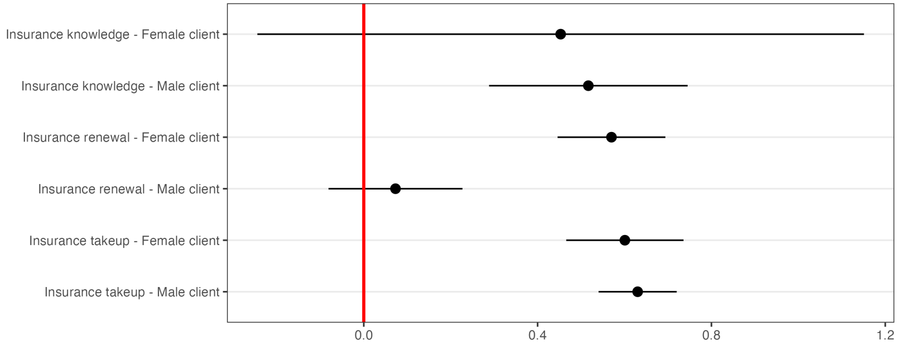
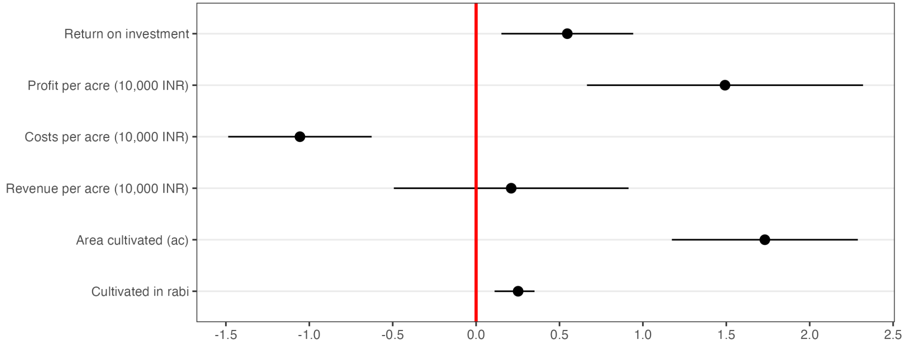


Treatment effects (LATEs) on agricultural outcomes (rabi)



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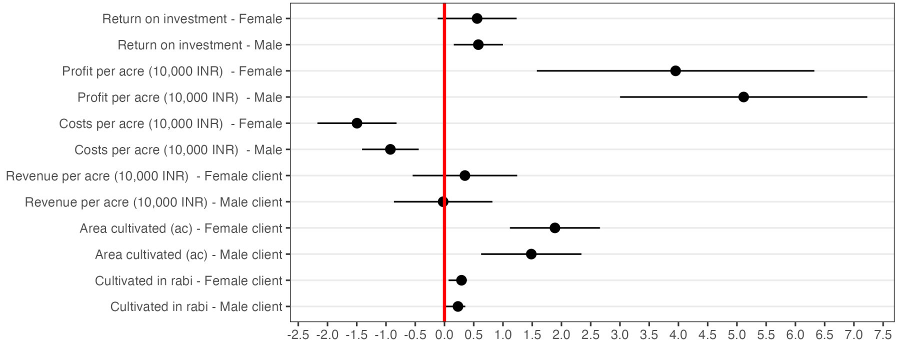
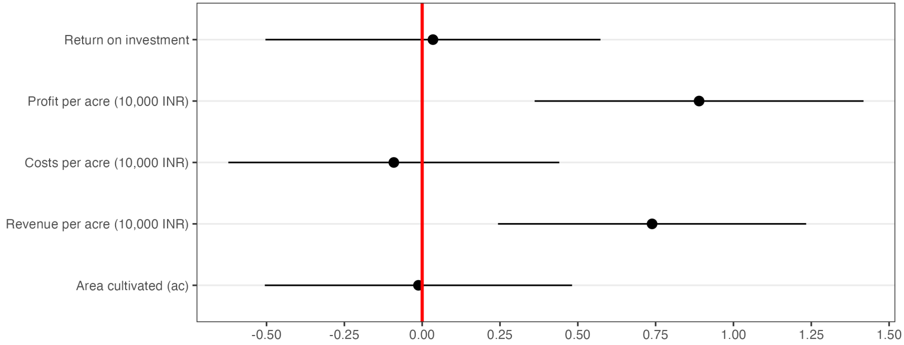


▸ Expenditures ▸ Household labor

Treatment effects (LATEs) on agricultural outcomes (kharif)



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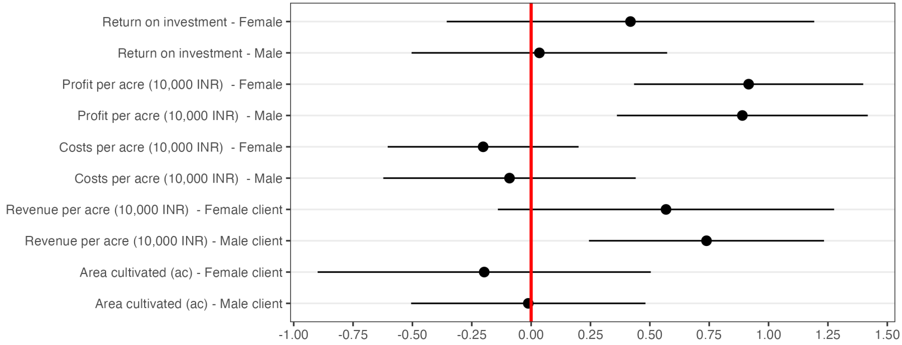

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  4. Gender findings and **heterogeneity** by **client** vs. **co-signees** illustrate the value of surveying men and women from the same household – not just male or female household head

Thank you!

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Parameter	Weight	Definition
Productivity	40%	Measurement of crop output per acre
Crop health change	20%	Measurement of crop vigor in terms of vegetative growth
Plant and soil moisture	15%	Measurement of water content and implied irrigation availability
Mechanical damage	13%	Measurement of damage due to natural calamities and other damages
Nutrients	7%	Availability of essential chemicals for the growth of the plant
Area	5%	Ease of doing cultivation

KhetScore credit-scoring methodology

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▸ Return

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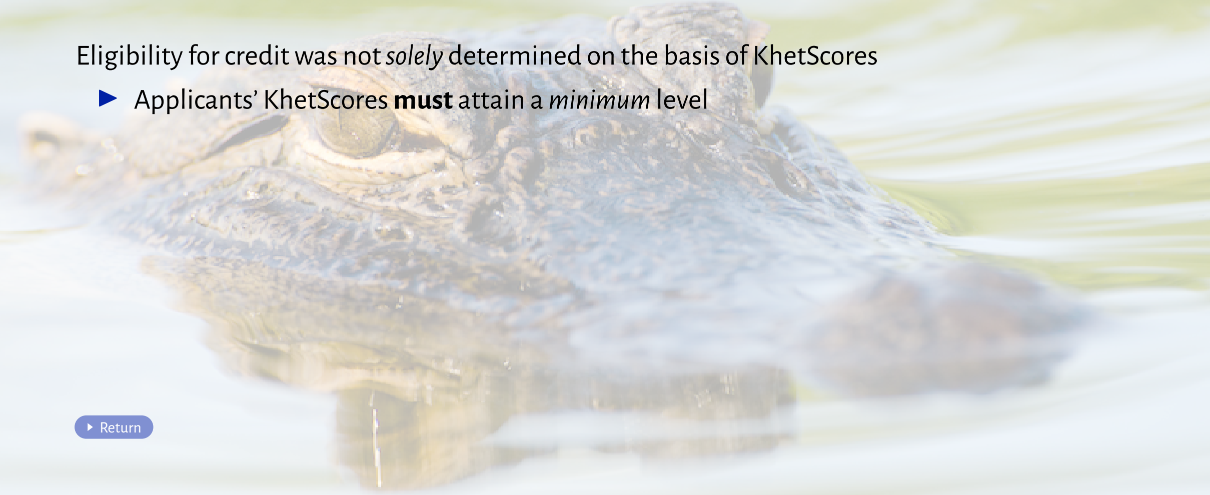

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- ...however, applicants may be *rejected* for a loan, *even if* they attain the *minimum* KhetScore

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KhetScore credit-scoring methodology

Eligibility for credit was not *solely* determined on the basis of KhetScores

- Applicants' KhetScores **must** attain a *minimum* level
- Applicants may qualify for a loan *even if* they do not have a credit score with a formal credit bureau...
- ...however, applicants may be *rejected* for a loan, *even if* they attain the *minimum* KhetScore
  - Discrepancies with KYC (Know Your Customer) check (verification of Aadhar card and bank details)

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  - Discrepancies with KYC (Know Your Customer) check (verification of Aadhar card and bank details)
  - Poor credit report with formal credit bureau
  - Seasonal discrepancies: farmers did not cultivate during the season for which the loan is being applied for (rabi/kharif) for three consecutive years

Return

Credit-insurance bundle

- Sum insured by PBI: INR 30,000 per acre
- PBI covered the following perils: excess rainfall, hailstorm, winds, animal attack, pests & diseases, landslide, and localized unseasonal rainfall
- Dvara staff took repeated (1x per week) images of insured land until harvesting
- Claims would be calculated by a group of independent agricultural experts who would anonymously review all images and declare the percentage of loss
- Based on calculation, pay-out would be triggered and eligible farmers would receive claim directly into their bank account

Implementation across four study seasons

Season/ Crop	(1) KhetScore loan offered	(2) Applied for KhetScore loan	(3) Received loan	(4) Enrolled in insurance	(5) Insurance payout made
Rabi 2020/21	900	90	62 (68.9%)	95	7
Kharif 2021	900	300	206 (68.7%)	445	10
Rabi 2021/22	900	350	319 (91.1%)	200	0
Kharif 2022	900	280	223 (79.6%)	430	0

- Limited availability of finance during COVID: implementation was very limited in the first season (Rabi 2020/21)
- Dvara was able to attract more financing from the private sector: increase in the number of clients reached, in terms of
  - The number of applicants
  - The percentage whose loans were approved
  - The number of farmers enrolled in insurance
- *Very few* farmers reported crop damage and filed insurance claims, resulting in few insurance payouts being made.
  - Impacts are *not* driven by *ex post* insurance payouts

Econometric specification: Intention-to-treat effects

- Main model for individual i from block b in period $t \in \{0, 1\}$:

$$Y_{ib,1} = \alpha + \beta Y_{ib,0} + \delta_1 Z_{ib} + X'_{ib,0}\Theta + \varepsilon_{ib}$$

- where
  - Y_{ib}: outcome measure at endline ($t = 1$) and baseline ($t = 0$)
  - Z_{ib}: binary indicator for random assignment to be offered credit + insurance bundle
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Econometric specification: LATE

- Only partial compliance: Individuals in the treatment group *select* into actually receiving treatment (taking up the credit + insurance product) ITT effects are not reflective of treatment effects among *actual* borrowers

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- Local average treatment effects (LATE): Rely on random assignment as instrument (Angrist and Imbens, 1995; Angrist et al., 1996)
  - Main model for individual i from block b in period $t \in \{0, 1\}$:

$$Y_{ib,1} = \alpha + \beta Y_{ib,0} + \delta_1 D_{ib} + X'_{ib,0}\Theta + \varepsilon_{ib}$$

  - where
    - D_{ib}: take-up of credit + insurance bundle

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  - First-stage regression:

$$D_{ib} = \gamma + \pi Z_{ib} + X'_{ib,0}\mu + \nu_{ib}$$

  - where
    - D_{ib}: take-up of credit + insurance bundle
    - Z_{ib}: random assignment to be offered credit + insurance bundle

Return

Econometric specification: Recursive bivariate probit

- Several outcome variables are binary
- LATEs of linear probability models can yield predicted probabilities outside the unit interval [0, 1]
- In addition, we have
  - A binary endogenous regressor (D_i)
  - A binary instrument (Z_i)
- Cannot use IV probit – not appropriate when endogenous regressor is binary

Econometric specification: Recursive bivariate probit model

Recursive bivariate probit model can be used when the endogenous regressor is binary

- First stage probit:

$$D_i = 1\left(\zeta_D + \pi Z_i + X_i'\Theta_1 + \varepsilon_i > 0\right)$$

- Second stage probit:

$$Y_i = 1\left(\zeta_Y + \delta D_i + X_i'\Theta_2 + u_i > 0\right)$$

- Endogeneity structure:

$$\begin{pmatrix} \varepsilon_i \\ u_i \end{pmatrix} \sim \mathcal{BN}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$$

Econometric specification: Recursive bivariate probit model

Local average treatment effects from recursive bivariate probit (Chiburis et al, 2011):

$$\Delta_{LATE} = \frac{[\mathcal{BN}(\zeta_D + \pi, \zeta_Y + \delta, \rho) + \mathcal{BN}(-(\zeta_D + \pi), \zeta_Y, -\rho)] - [\mathcal{BN}(\zeta_D, \zeta_Y + \delta, \rho) + \mathcal{BN}(-\zeta_D, \zeta_Y, -\rho)]}{\Phi(\zeta_D + \pi) - \Phi(\zeta_D)}$$

- In our models, $\zeta_D = \zeta_Y = 0$, so this simplifies to

$$\Delta_{LATE} = \frac{[\mathcal{BN}(\pi, \delta, \rho) + \mathcal{BN}(-\pi, 0, -\rho)] - [\mathcal{BN}(0, \delta, \rho) + \mathcal{BN}(0, 0, -\rho)]}{\Phi(\pi) - \Phi(0)}$$

Heterogeneous LATEs

- Heterogeneity by gender of client: ▸ Return

Heterogeneous LATEs

- Heterogeneity by gender of client: Return
  - Instrument for D_{ib} and $D_{ib} \times Female_{ib}$ with Z_{ib} and $Z_{ib} \times Female_{ib}$

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Heterogeneous LATEs

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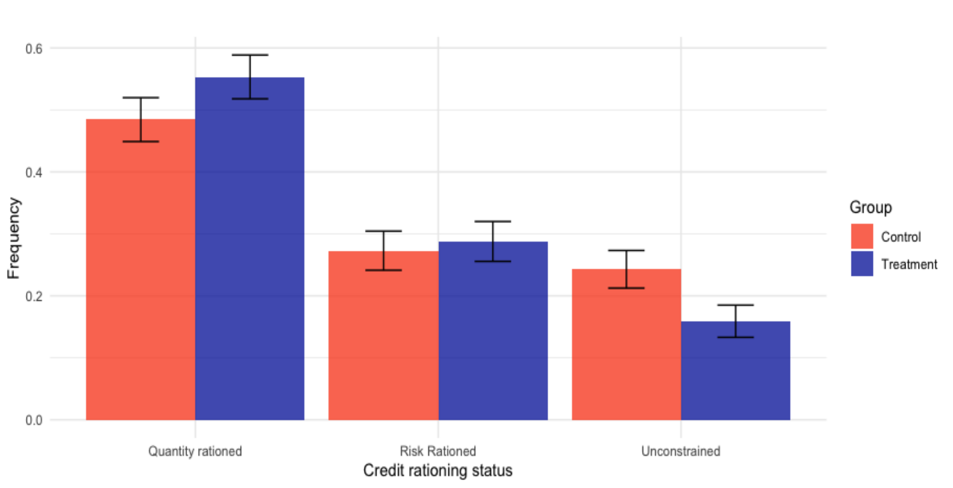
- Heterogeneous LATEs for binary dependent variables:
  - Estimate recursive bivariate probits and compute LATEs for heterogenous sub-samples

Credit rationing – Dvara E-Registry clients



Return

Familiarity with concepts related to crop insurance

Respondents were asked to indicate whether the following statements were true or false

1. I have to pay a premium to be covered by crop insurance
2. The insurance premium is typically a small fraction of the maximum insurance payout in case of damage
3. Crop insurance promises to pay compensation every season
4. Crop insurance promises to pay compensation for any amount of loss I may face for any reason
5. If I don't have any crop damage, the insurance company gives back my premium
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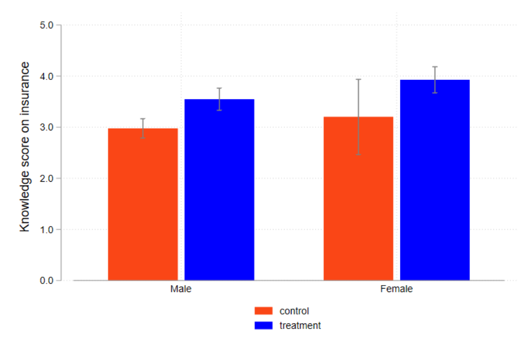

▸ Return

The treatment *not only* increased insurance take-up, but *also* understanding of how insurance works.

Treatment effects on empowerment – Main client

	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**
Std. Error	(0.039)	(0.042)	(0.049)	(0.053)	(0.017)
Treatment | Female	0.278***	0.252***	0.057	0.072	0.023
Std. Error	(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	0.45	0.803	0.716	0.893

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 labour. Each regression controls for baseline levels of dependent variable. All specifications include a dummy variable for block, a dummy variable indicating whether the client had taken credit in the 12 months prior to the baseline survey, and profits per acre at baseline.

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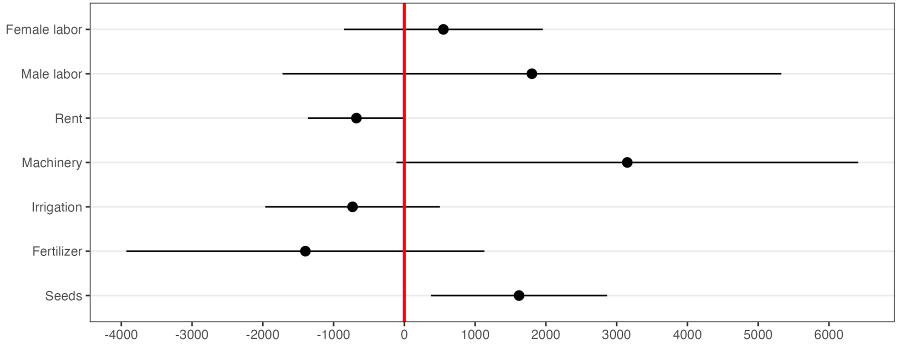
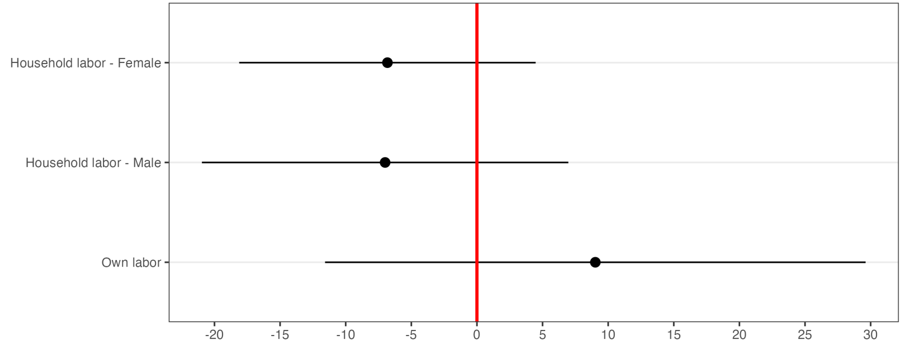
Treatment effects (LATE) on agricultural expenditures (rabi)



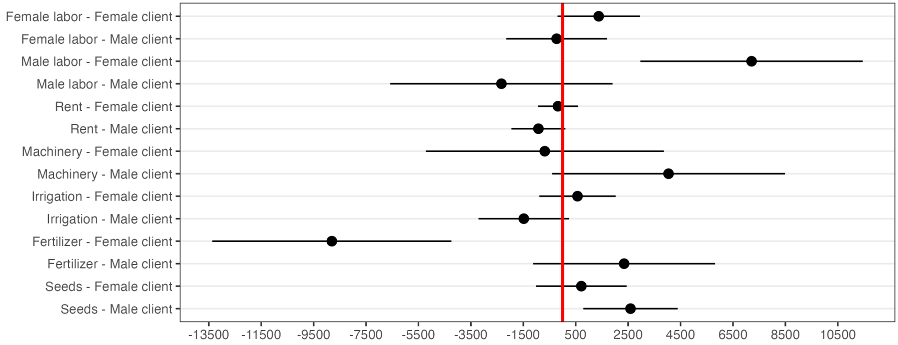
Return

Treatment effects (LATE) on household labor (rabi)



Return

Treatment effects (LATE) on agricultural expenditures (rabi) by gender



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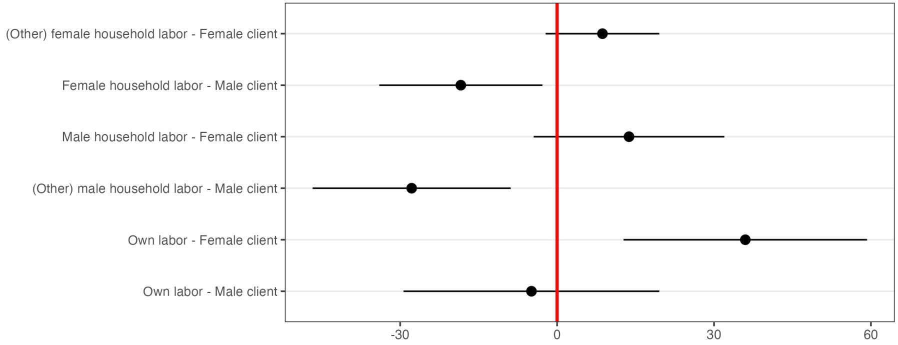
Treatment effects (LATE) on household labor (rabi) by gender



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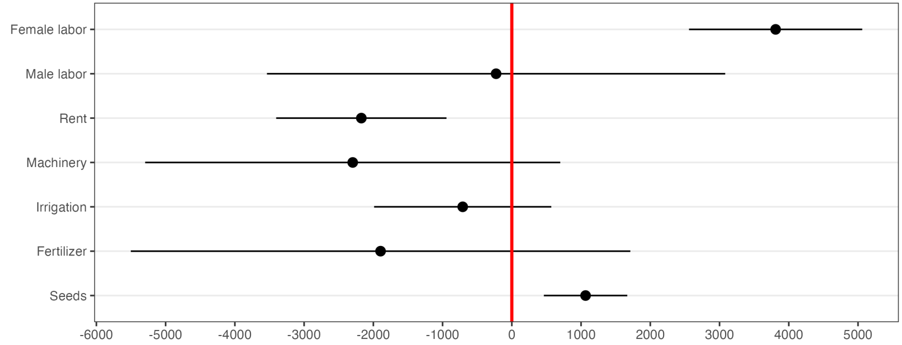
Treatment effects (LATE) on agricultural expenditures (kharif)



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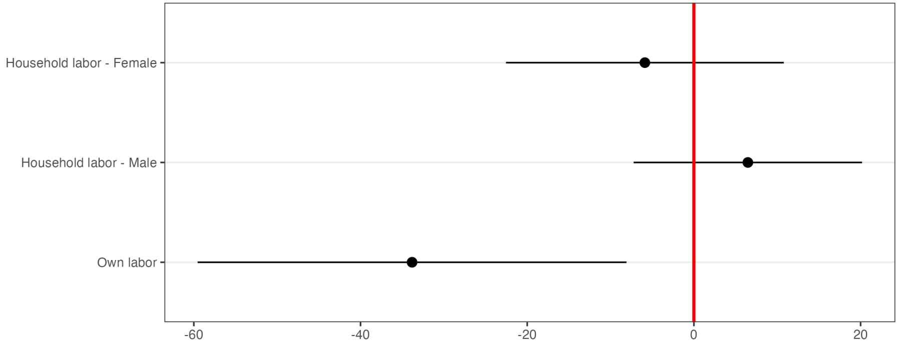
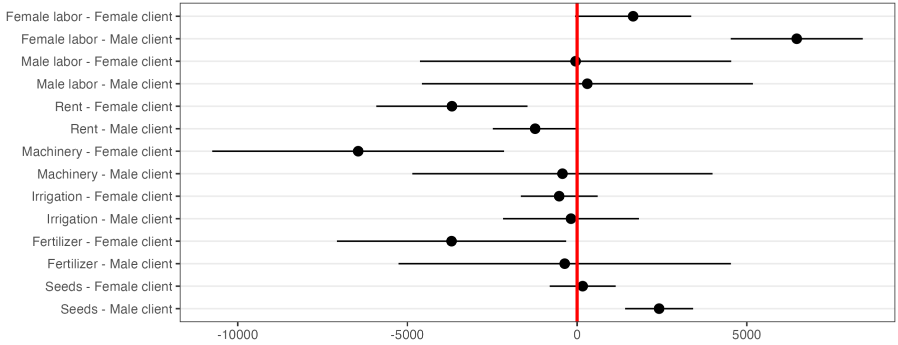
Treatment effects (LATE) on household labor (kharif)



Return

Treatment effects (LATE) on agricultural expenditures (kharif) by gender



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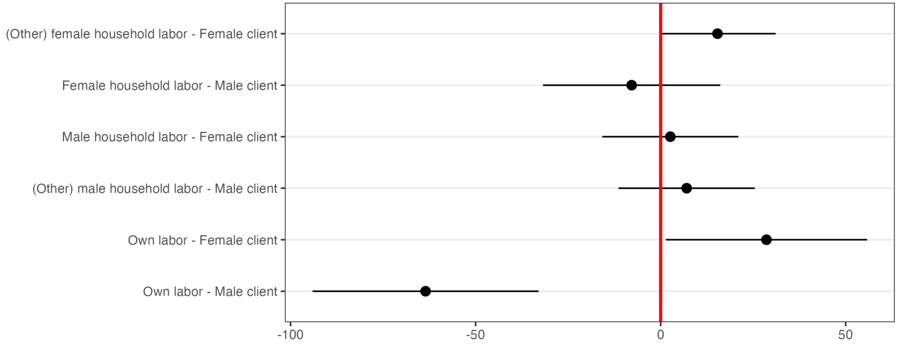
Treatment effects (LATE) on household labor (kharif) by gender



▸ Return

Treatment effects on empowerment - Other household member

	Borrow decision	Use of borrowed funds	Input in livelihoods	Control use of income	Asset ownership
	(1)	(2)	(3)	(4)	(5)
Panel B. Other family member					
Treatment | Male	-0.067	-0.028	-0.06	-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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Cost per acre, return on investment, and profit per acre all estimated excluding own labour. Each regression controls for baseline levels of dependent variable. All specifications include a dummy variable for block, a dummy variable indicating whether the client had taken credit in the 12 months prior to the baseline survey, and profits per acre at baseline.

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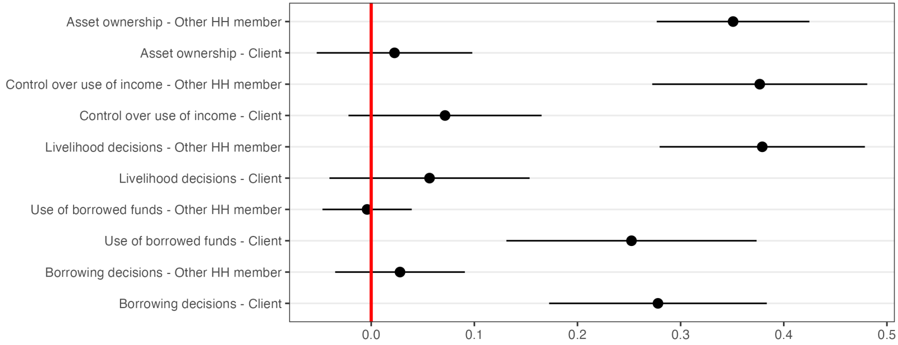
Treatment effects on women's empowerment



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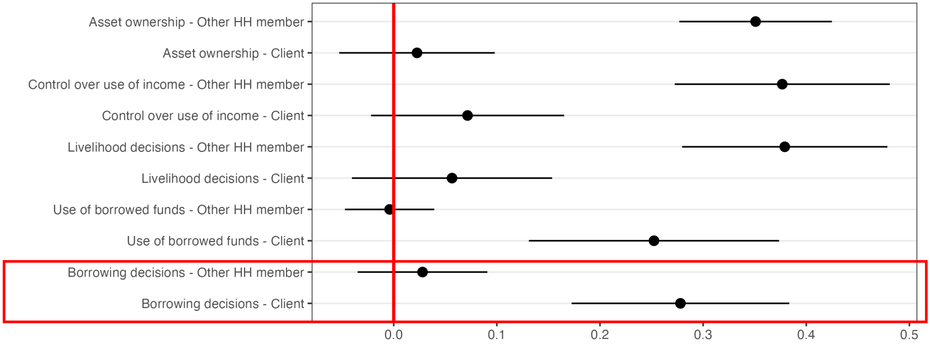
Treatment effects on women's empowerment



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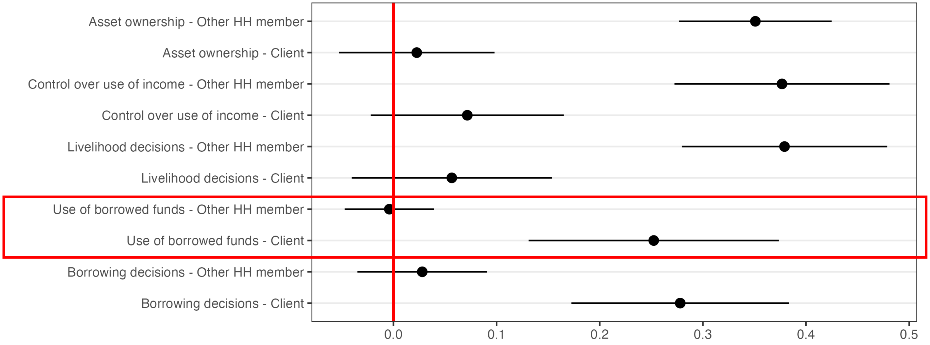
Treatment effects on women's empowerment



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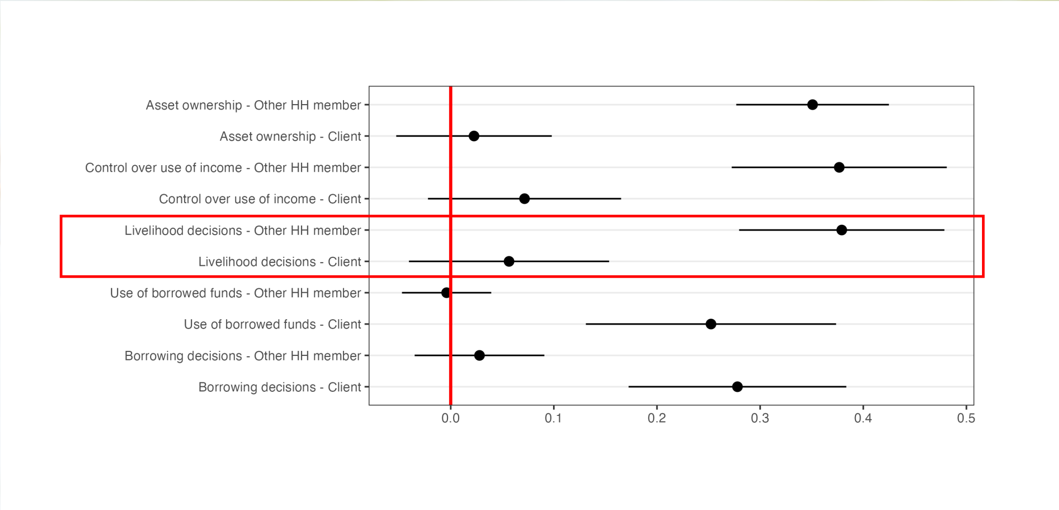
Treatment effects on women's empowerment



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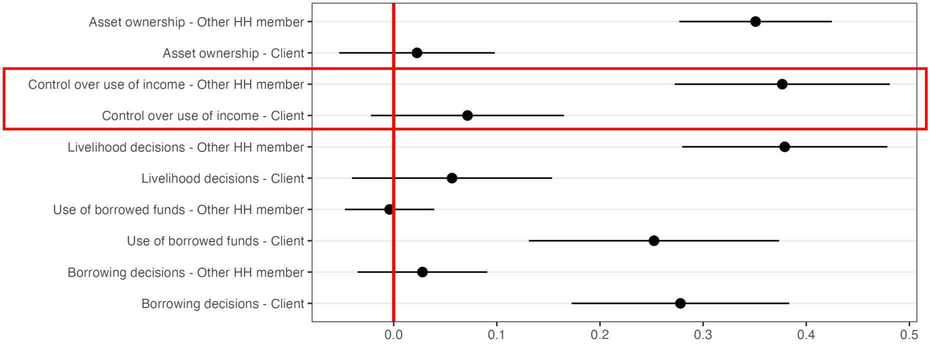
Treatment effects on women's empowerment



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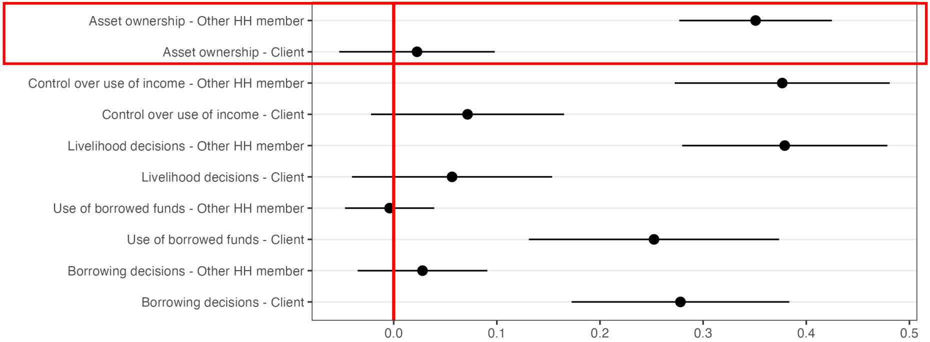
Treatment effects on women's empowerment



▸ Return

Perceived stress among women

For each question, respondents chose from the following alternatives:

1: Never	2: Almost never	3: Sometimes	4: Fairly often	5: Very often

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2. How often have you felt confident about your ability to handle your personal problems?

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2. How often have you felt confident about your ability to handle your personal problems?
3. How often have you felt that things were going your way?

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During the last month...

1. How often have you felt that you were unable to control the important things in your life?
2. How often have you felt confident about your ability to handle your personal problems?
3. How often have you felt that things were going your way?
4. How often have you felt difficulties were piling up so high that you could not overcome them?

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- For questions 1 and 4, higher scores indicate increased levels of stress
- For questions 2 and 3, higher scores indicate lower levels of stress

Perceived stress among women – Primary client

	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	0.05	0.269	0.369*	0.286*	0.22
	(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	1.78	1.648	1.309

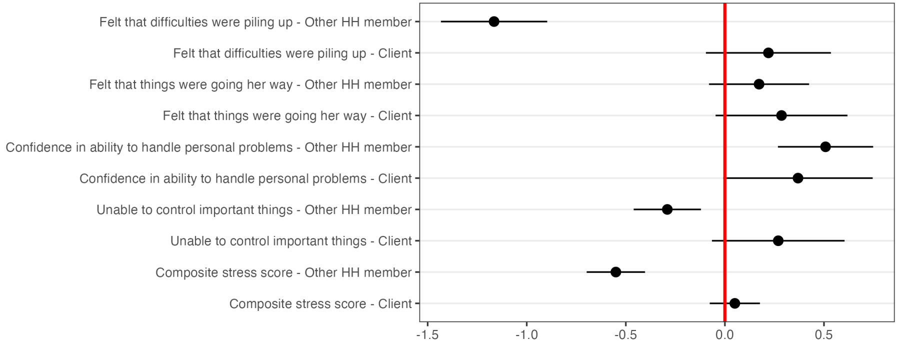
Notes: Standard errors in parentheses clustered by village. *** p < 0.01, ** p < 0.05, * p < 0.10. Cost per acre, return on investment, and profit per acre all estimated excluding own labour. Each regression controls for baseline levels of dependent variable. All specifications include a dummy variable for block, a dummy variable indicating whether the client had taken credit in the 12 months prior to the baseline survey, and profits per acre at baseline.

Perceived stress among women – Other household member

	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 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Cost per acre, return on investment, and profit per acre all estimated excluding own labour. Each regression controls for baseline levels of dependent variable. All specifications include a dummy variable for block, a dummy variable indicating whether the client had taken credit in the 12 months prior to the baseline survey, and profits per acre at baseline.

Treatment effects on perceived stress among women



Return