Rural Banks Can Reduce Poverty: Experimental Evidence from 870 Indian Villages*

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Abstract

We evaluate an at-scale experiment that randomized branch placement by a private-sector bank across 870 South Indian villages. Within two years of branch opening, one in three households in treated villages had taken a formal loan and roughly a quarter had taken up an insurance or savings product. Survey data show a 10% reduction in informal borrowing levels. These changes impact individual and aggregate well-being: Relative to control villages, poverty rates in treatment villages are 8% lower and are accompanied by reductions in psychological stress. Alongside, occupational diversification and village economic activity rise: households in treated villages are 7% more likely to have a member working in non-agriculture self-employment, have 20% higher business income, and 6% higher wage income. Our evidence is consistent with a model of entrepreneurship in which access to cheaper formal credit increased village-wide labor demand.

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1 Introduction

Motivated by the twin beliefs that access to formal finance is essential for rural development and that rural markets are likely unprofitable for private sector banks, governments in many newly independent low income countries mandated public sector banks to serve rural markets (La Porta et al., 2002). While there is evidence of 'social banking' reducing rural poverty (Burgess and Pande, 2005; Bruhn and Love, 2014; Célerier and Matray, 2019), politically motivated lending typically limited their profitability and, ultimately, their sustainability (Cole, 2009).[1] More recently, the main competition for rural informal lenders has increasingly come from NGO-led microfinance programs[2] and, in some cases, asset and cash grant programs. Experimental evidence on the positive impacts of these programs on rural economic activity point to the importance of aggregate demand and business investment. This suggests that the transformational impacts of rural formal finance are more likely to occur when it is available at scale (Breza and Kinnan, 2018; Egger et al., 2019; Kaboski and Townsend, 2012).[3]

These findings raise anew the possibility that bank branches that service relatively large service areas and provide a wide range of financial products (credit, savings, insurance) may be critical for rural development. Rapid economic growth over the last few decades in countries like India also suggest rural areas in these countries may be viable markets for private sector banks. Indeed, since 2000, India has seen a sharp expansion in private sector banks (Indian Banks' Association, 2021).[4] Relative to public sector banks, these banks are relatively free of political constraints in choosing their clients and their operations are more financially sustainable than grant-based programs. However, whether these private banks can reduce poverty and be engines of growth is questionable - they may for instance, 'cream-skim'

[1]Cross-country evidence has tended to support the belief that access to finance is a key determinant of economic growth and poverty reduction (King and Levine, 1993; Rajan and Zingales, 1998; Levine, 2005; Beck et al., 2007).

[2]The volume of credit lent to Self-Help Groups, which are formed through NGO and government programs to disburse microcredit loans, increased by almost 70% between 2009 and 2013, Nair and Tankha, 2013

[3]In contrast, partial equilibrium effect of microfinance is mixed (Banerjee et al., 2015; Angelucci et al., 2015; Meager, 2019)

[4]For example, from 2015 to 2021, the credit market share of private banks rose from 21% to 37%.

clients. This could both cause the poor to face higher interest rates from informal lenders and fail to sufficiently expand aggregate demand and business investment.

To evaluate these trade-offs, we provide evidence from an at-scale randomized rural bank expansion in South India. In collaboration with a private sector bank, we coordinated the roll-out of 50 brick-and-mortar microfinance bank branches across almost 900 rural villages in South India. Our partner bank randomized branch placement across pairs of potential service areas. Each service area encompassed 5-12 unbanked villages. Our analysis leverages two extensive socioeconomic surveys and biomarker measurements conducted on a sample of 4,160 households roughly two years after the branch expansion.

Households in treatment villages report 13% higher monthly income and an increase in asset ownership of +0.03 standard deviations relative to control households. A biomarker based stress index (assayed from hair samples) is significantly lower for treatment households. Thus, it appears that even for a poor population that has limited experience with formal borrowing, the mental health benefits of easing liquidity constraints outweigh potential negative impacts on stress of formal debt.[5]

An important summary measure is the 8% lower rate of poverty in treated compared to control villages, indicating substantial welfare gains to relatively poor households of banking services in rural areas.[6] This is striking since our partner lender offered standard "entrepreneurial" group loans designed to bolster investment among profitable microentrepreneurs. Although borrowing increased among households in the lowest income tercile, these loans were used primarily to finance consumption rather than investment (Kaboski and Townsend, 2012). Households in the lowest tercile of the income distribution, who are

[5]Although easing liquidity constraints might reduce stress by improving a household's financial position, access to credit might also increase stress if indebtedness itself is anxiety-inducing. This would be particularly likely if bank access leads to over-borrowing, reputation concerns or social pressure to repay, as have been documented in other settings.

[6]We measure poverty rates as poverty headcount ratio based on the World Bank's $ 1.90 a day per person threshold. Since the $ 1.90 threshold is expressed in 2011 PPP, we first use the $ - Indian Rupees 2011 PPP (15.550 Indian Rupees per dollars). We then adjust this for the rate of inflation (through the Consumer Price Index, CPI) using 2010, the start of our study, as our base year.

primarily agricultural wage laborers, were unlikely to obtain entrepreneurial loans.

Consistent with theoretical and empirical research, we hypothesize that banking services benefit the poor (and thereby lower poverty) by relaxing credit constraints for higher income entrepreneurial borrowers (Banerjee and Newman, 1993; Aghion and Bolton, 1997; Evans and Jovanovic, 1989), whereby the relaxation of financial constraints promotes investment among better-off households (Banerjee et al., 2019) and generates higher labor demand.

Rich data on village economic activity allow us to evaluate these dynamics by investigating the pattern of impact of bank access across the income distribution. Two results indicate a "trickling-down" to poorer households of the direct economic gains from banking services provided to better-off households. First, better-off households increased formal borrowing for farming and business investment. Moreover, increased borrowing for productive purposes among the relatively wealthy was associated with business growth in the village economy: business investment and business sales in treated villages are 18% and 20% higher than in control villages two years after banking services were introduced, confirming that relaxing liquidity constraints promotes investment and entrepreneurship. We also observe that access to formal loans generated job opportunities for poorer individuals: households in treated villages are 33% more likely to employ non-household members in business activities. Finally, agricultural wages in treated villages are significantly higher, pointing to increased local labor demand.

While formal borrowing does rise among poorer households, their loans are used for consumption and education rather than in business. Importantly, the stress effects are found among both the top and the bottom terciles, consistent with the patterns of income gains across the income distribution.

Taken together, our findings provide novel experimental evidence on the direct and indirect channels through which rural banks can reduce poverty. Diversification by better-off households out of the agricultural sector generates a "trickle-down" effect onto poorer households through higher labor demand both inside and outside of agriculture. The findings demonstrate a causal impact of access to credit on occupational diversification - arguably, the first step towards the structural transformation of an economy. Finally, the bank's annual report for 2015-16 (which corresponds to our last endline round) shows that rural expansion was financially sustainable - the company grew its business in all South Indian branches profitably.

On rural welfare, our finding corroborate quasi-experimental evidence from social banking policies (Burgess and Pande, 2005; Kaboski and Townsend, 2012; Bruhn and Love, 2014). We extend the literature by studying the mental health effects of formal debt, an outcome that is particularly pertinent to developing countries (Mullainathan and Shafir, 2013; Schilbach et al., 2016). While the effects of poverty alleviation on mental health has been assessed in the context of cash grants (Haushofer and Shapiro, 2016), the predicted impact of access to credit on mental wellbeing is more ambiguous (Fernald et al., 2008). Our results reveal that, in fact, banks can reduce poverty in underserved areas without significant negative effects on mental health. Methodologically, our stress analysis innovates by using hair samples from almost 3,000 subjects. In doing so, we provide one of the largest empirical analyses of sex-hormone data in any setting and one of the very few in a developing country context (Walther et al., 2019).

2 Setting and Empirical Predictions

2.1 KGFS Expansion and Experimental Design

Our study partner in this study was Kshetriya Grameen Financial Services (KGFS), a private-sector financial company that provides credit through brick and mortar branches.[7] It follows an inclusive approach whereby no specific population segment is targeted, and no specific

[7]The current name of the bank is 'Dvara KGFS'.

eligibility requirement exists for prospective customers.[8]

Although KGFS offers several financial products to its customer base (including loans, insurance, and savings), its core financial product is microcredit, in particular, joint-liability group (JLG) loans. KGFS JLG loans are targeted almost exclusively to women, as is traditional in this sector, and range in size from Rs. 10,000 in the first loan cycle ($\approx$ \$150) to Rs. 25,000 ($\approx$ \$350) in consequent loan cycles, amounts similar to JLG loans provided by other Indian MFIs.

While KGFS has much in common with other MFIs, it should be noted that it is a private, for-profit banking initiative, in contrast to, for example, the Indian Social Banking Initiative studied by Burgess and Pande (2005). As such, it has proven to be a fully sustainable model of village banking which grew its business profitably in almost all branch units over the last decade.

2.1.1 Experimental Design

In order to rigorously document the economic and social impact of the financial services KGFS provides to its rural customer base, its administration first worked with the research team to identify 100 service areas in three districts of rural Tamil Nadu where they were planning to expand coverage (Ariyalur, Pudukkottai and Thanjavur). To maximize statistical power, service areas were paired by the researchers according to geographic location

[8]When a new branch opens, KGFS visits *all* households in the village to inform them about its services and organizes an "awareness meeting" in each of the village centers. The meeting usually lasts 30 to 60 minutes – our field team, who also attended a few of these meetings, noticed that attendance by the village population was quite high. During the meeting, the bank staff would hand out brochures to advertise their services and products. The meeting is intended to introduce the KGFS model to the village, to illustrate the details of the financial products and services offered by KGFS, and to share information on the branch location and relevant contact details.

and observable characteristics of the catchment population, and then the opening of a bank branch was randomly assigned within each pair.[9] Between 2010 and 2012, the bank proceeded to open new branches in 50 randomly chosen service areas, and refrained from doing so for at least two years in the corresponding control service areas.[10]

Figure 1 shows the location of each of the 50 pairs of service areas included in our study. Each bank branch service area covered approximately 10,000 people (2,000 households) living in 5-12 villages within a 4-5 km radius. Two rounds of socioeconomic surveys and biomarker measurements were conducted with approximately 40 households in each service area, prior to branch opening (baseline) and two years after opening (endline). Household sampling accounted for the entire village population distribution in each service area, allowing our study to estimate the impacts of KGFS expansion on the village economy as a whole.

2.2 The impact of rural banking

Our experiment is unique as it allows us to study the economy-wide impacts resulting from large capital injections in rural village economies. There are two main channels – direct and indirect – through which the relaxation of credit constraints may impact poverty and in turn, generate downstream impacts on wealth and psychological wellbeing.

Standard models of credit and entrepreneurship (Banerjee and Newman, 1993; Aghion and Bolton, 1997; Evans and Jovanovic, 1989) predict that the relaxation of financial constraints among the poor increases investment in self-employment activities hence earning capacity.

[9] In particular, in an effort to minimize differences between treatment and control groups, we used Edmond's algorithm for minimum distance matching to construct pairs of service areas. Details on the variables included in this matching algorithm are provided in the AEA RCT Registry: https://www.socialscienceregistry.org/trials/116.

[10] The primary considerations for inclusion as a feasible service area were adequate access to road and electricity infrastructure, and population density.

Randomized evaluations of microfinance programs have shown that these effects are concentrated among better-off households (Banerjee et al., 2019) who are best positioned to gain from entrepreneurial loans. This evidence suggests that an increase in credit availability may positively impact investment and hence household income through a direct effect on wealthier borrowers.

Increased access to credit may also have general equilibrium effects. For example, Breza and Kinnan (2018) have documented that the credit supply reduction resulting from the Andra Pradesh microfinance crisis led to a decrease in wages and consumption. Their results imply that village-level injections of formal credit may expand local economic activity even when poorer households do not use loans for investment (Lloyd-Ellis and Bernhardt, 2000; Ghatak et al., 2007). By enabling better-off households to shift out of the agricultural sector and invest in microenterprises, an increase in credit supply may generate spillover effects on job opportunities for lower-income households, who are primarily agricultural wage laborers in rural areas. Hence, the impacts of bank access "trickle-down" onto poorer households through higher labor demand both inside and outside of agriculture.

The direct and indirect channel can coexist and interact with each other. For example, as investment in self-employment activities increases in response to reduced credit constraints, business revenues and household income increase for wealthier households. At the same time, new employment opportunities are created, generating income gains for poorer households.

Both the direct and the indirect channel predict an expansion in local economic activities in response to an increase in cheaper, formal credit availability. As businesses expand, wage employment and wage earnings increase. To the extent that general equilibrium effects are at play, we should expect a fall in poverty and an increase in wealth (e.g., household assets) across the income spectrum.

While the results from both the RCT literature and quasi-experimental research on social banking provide support to the positive relationship between access to credit, income and wealth (Burgess and Pande, 2005; Banerjee et al., 2015; Angelucci et al., 2015), the impact of banking services on mental health remains ambiguous (Fernald et al., 2008; Karlan and Zinman, 2010). On the one hand, easing liquidity constraints may improve a household's financial position and hence reduce stress; on the other hand, access to credit may deteriorate mental health if indebtedness itself is anxiety-inducing (Sweet et al., 2013). The net effect of rural banking on mental health will likely depend on the direct and indirect benefits of increased borrowing in the local village economy.

In the next sections, we detail the data and empirical strategy to validate our empirical predictions.

3 Data and Empirical Strategy

3.1 Data

We use the randomized expansion of KGFS bank branches to obtain causal estimates of the impact of access to finance at the village level. First we discuss our sampling strategy. We then discuss our outcome data. Finally we discuss our identification model.

3.1.1 Study Sample

In each of the 100 service areas identified for KGFS expansion, we sampled 46 households for a total of 4,684 households in the core analysis sample. Baseline data collection occurred alongside branch expansion, between 2010 and 2014 (in three different rounds), and endline surveys were administered between 2013 and 2016 (again, in three different rounds).

We managed to successfully reach 4,480 and 4,575 households at baseline and endline, respectively. Of these, 4,207 households were surveyed at baseline and 4,184 households were surveyed at endline.[11] Figure 2 provides a graphic representation of the study sample at endline.[12] We excluded 24 households at endline who did not answer/refused to report information on their loans, a key outcome in our study, leaving us with a final analysis sample at endline of 4,160 households. Whenever possible, we augment the core sample with data from an additional 10,201 households living in the same villages as our study sample for which we have limited information on income, poverty and employment.

Survey Data Our baseline and endline surveys collected detailed information on the socio-economic profile of the core sample, including: household income and assets; outstanding and repaid loans, savings accounts and any insurance products; household members' occupation and employment (wage labor or self-employment), and business outcomes (business sales and employment in the business).

At baseline, our sample population was relatively poor, with roughly half of households be-

[11] Reasons for not being surveyed include inability to identify the household, survey participation refusals, migration, failure to identify a suitable respondent in the household. Balance checks on attrition rates are shown in Table A2 in the Appendix. 3,859 households in the core sample were surveyed both at baseline and at endline. There is no significant difference either in the share of households that were surveyed at baseline but not at endline or in the share of households that were surveyed at endline but not at baseline.

[12] The selection of households generally followed a two-stage design to account for clustering of households in villages, while ensuring that the sample was representative of the chosen service areas. The first stage employed a probability proportional to size (PPS) sampling of villages within service areas. That is, villages were drawn to be included in the sample according to their relative population size. Additionally, the center village with the intended branch location was included. Each service area was allocated 46 baselines which were divided evenly into portions, and villages were drawn to be included in the sample according to their relative population size. In stage two, the listing was conducted with a 5-household skip in all villages sampled during stage one, collecting residential addresses and information for identification purposes, such as names and occupations of household members. We dropped all households that did not include a woman between the ages of 18 and 55. We then randomly selected the number of households in each village that had been determined in stage one.

low the poverty line, and had average monthly per capita income of 1,600 Rs (approximately $\approx$ \$105 in 2011 PPP), as shown in Table 1.[13] Yet, households' engagement with the financial sector, particularly with the informal one, was quite high. About 70% of the households in our study sample had an outstanding loan with an informal lender before the expansion of KGFS.[14] A lower, but still non-negligible share of households (around 55%), also borrowed from the formal financial sector, and predominantly from state-run banks.[15] All in all, more than half of households' total borrowing at baseline was from informal sources, as Table 1 indicates. Informal loans were also substantially more expensive than formal ones. In terms of occupations, Table 1 shows that 62% of study households had at least one member working in agriculture at baseline. At the same time, less than one in five households (16%) reported having at least one member being self-employed. These statistics indicate that the expansion of KGFS took place in predominantly rural areas with a very large share of the population being engaged in agricultural activities. Besides, despite KGFS expanded in areas where households were fairly familiar with financial services and products, the low level of self-employment at baseline is suggestive of binding financial constraints in our study population.

[13]Poverty is measured using using the headcount poverty ratio definition from the World Bank (poverty line of 1.90 USD per day per capita, expressed in Rs. 2011 PPP, revised using 2010 as CPI base year). Our survey asked each household to estimate their income over the last 30 days. We then converted the 30-day income into real term using 2011 CPI with base year 2010, calculated household income per day, and divided by household size. Table A5 provides detailed variables definitions.

[14]We classify as informal lending sources: friends, neighbors, relatives, shopkeepers, employers, moneylenders, pawn brokers, landlords, rotating savings groups (ROSCAs) or other savings group, Chitfunds, and Financiers, Religious Trusts (e.g., Panchayat Kovil Trust).

[15]At baseline, 20% of households had at least one loan from nationalised banks. The second and third more frequent formal borrowing source at baseline were Primary Agricultural Credit Societies (PACS) and Cooperative Banks (10.3%) and Self-Help Groups (8.7%) This is in line with studies showing that government banks dominate formal lending particularly in low-income countries with poor financial systems (La Porta et al., 2002)

Table 1: Summary Statistics of HH-level Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: Demographics					
Household Head is Male	0.72	0.45	0	1	4066
Years of Education of Household Head	7.49	4.84	0	19	4066
Number of Household Members	4.52	1.87	1	16	4066
Most Backward Caste /					
Scheduled Caste and Tribe	0.59	0.49	0	1	4066
Household Owns Land	0.55	0.5	0	1	4064
Panel B: Income, Poverty and Consumption					
Per capita HH Income (30-day)	1583.91	2481.45	0	51993.08	2727
Below Poverty Line (using Income)	0.55	0.5	0	1	2725
Per capita HH Consumption (30-day)	768.12	573.66	0	6125.67	4063
Panel C: Borrowing					
Household has Outstanding Formal Loans	0.56	0.5	0	1	4052
Household has Outstanding Informal Loans	0.71	0.45	0	1	4052
Informal Borrowing over Total Borrowing	0.56	0.41	0	1	3230
Panel D: Occupations					
At Least 1 HH Member Works in Agriculture	0.62	0.49	0	1	4066
At Least 1 HH Member is Self-Employed	0.16	0.37	0	1	4063

Note: Summary statistics of main demographics, income, poverty and consumption, borrowing and occupations for the core household sample. Per capita HH income, per capita HH consumption have been topcoded, 3 standard deviations from the mean. The share of informal borrowing over total borrowing is computed by taking the ratio between households' total outstanding informal borrowed amount in the past 24 months and total outstanding borrowed amount in the past 24 months. Both total outstanding informal borrowed amount and total outstanding borrowed amount have been topcoded, 3 standard deviations from the mean.

Administrative Data We complement self-reported indicators of borrowing, saving, and insurance use from our core household sample with customer-product level administrative data from KGFS' Customer Management System (CMS). These data are used to compute and track take-up rates of KGFS products through time.

Stress Biomarkers In addition to survey data, we collected at endline hair samples from 3,241 eligible women in core households after obtaining their consent for hair collection (476 respondents refused to provide hair for laboratory analysis). These were sent for laboratory analysis of hormone content in order to measure physiological stress responses.[16] Laboratory

[16]Most of the survey was administered to the household head. However, two sections on health and

assays of hair samples measured stress biomarkers including cortisol, cortisone, and dehydroepiandrosterone (DHEA).[17] Viable laboratory measurements for cortisol and cortisone were obtained for 2,952 and 2,966 of these women, respectively.[18] DHEA assay was not conducted until a midway through the endline data collection, which meant that DHEA levels were only measured for 2,091 of the women who provided hair samples.[19]

Stress biomarkers represent "objective" measures of mental health. Cortisol and DHEA in particular are released by the adrenal glands in response to stress. Importantly, compared with saliva or serum, biomarkers obtained from hair samples reflect integrated hormone secretion over the 3-month period prior to hair sampling versus a one-day as in the case of saliva (Stalder and Kirschbaum, 2012). By employing these laboratory measurements as indicators of mental health, we are able estimate the impacts of formal financial access on individuals' chronic stress.[20]

wellbeing and biomarkers collection were specifically administered to a woman in the household who was chosen according to a distinct algorithm. The collection of stress biomarkers from women in the sample is motivated by the fact that the main KGFS product is a JLG loan specifically targeting women hence it is likely that women's wellbeing was directly affected by the expansion of KGFS.

[17]The following criteria were used to select a woman in each household for inclusion in the health modules (in order of priority): (i) being the mother of the youngest child, with husband staying in the same household; (ii) being the youngest married women, with husband staying in the same household; (ii) other married woman, with husband staying in the same household; (iv) other married woman in the household. In addition, in order to be interviewed, the woman had to be aged between 18 and 55, and she had to live in the household for at least six months in the past year.

[18]No biochemical measurements could be performed on 273 samples as they contained an insufficient amount of hair or insufficient quality. For instance, due to the transport, a clear cut point of the sample was no longer visible and the hairs were loosely arranged not allowing to identify the necessary scalp-near 3-cm hair. For two samples, the laboratory reported valid cortisol, but missing values of cortisone. Of the 2,968 cortisol measurements, for six cases (0.2%) a non-detectable value was reported from the laboratory, while zero non-detectable values were reported for cortisone.

[19]Of these 2,091 DHEA measurements, for 124 cases (5.9%) a non-detectable value was reported from the laboratory.

[20]The hair sampling procedure consisted in cutting the woman's hair strand as close as possible to the scalp from a posterior vertex position. A minimum of 20 mg of hair was obtained from each participant in order to provide sufficient material for biochemical analysis. Hair samples were then sent to the Dresden LabService GmbH, where the first scalp-near 3 cm hair segment was used for analyses. Samples were collected from participants regardless of usage of hair products, while different hair treatments (e.g. hair dying, usage of hair oil) or other factors (e.g. location of obtained hair sample at vertex position, regular usage of cortisol cream) that could affect hair steroid concentration were assessed by self-report. Hair steroids were determined via liquid chromatography tandem mass spectrometry (LC–MS/MS) according to the protocol by Gao et al. (2016). For more technical details we refer to Walther et al. (2019).

3.2 Empirical Strategy

We evaluate the impacts of access to rural banks by estimating the following regression:

$$y_{ik} = \beta_0 + \beta_1 T_k + \beta_2 S_k + \delta_{pk} + x'_{ik} + \epsilon_{ik} \tag{1}$$

where y_{ik} is the outcome of interest for household i living in service area k in pair (stratum) p.[21] T_k is the treatment dummy indicating whether household i lives in a treated or control service area, and S_k are survey-round dummies.[22] δ_{pk} are service areas-pair fixed effects to account for randomization strata. The vector x_{ik} contains household-level controls measured at baseline and selected using double LASSO regression (Belloni et al., 2014). Standard errors are clustered at the service area level, the unit of randomization. Our main coefficient of interest is β_1, which is the average intent-to-treat (ITT) effect of village banks. However, since our focus also lies in identifying which population segment are most affected by formal financial access, for a number of outcomes we also look at heterogeneous treatment effects of households' initial monthly income levels. We divide our sample into income terciles, and estimate the following regression:

$$\begin{aligned} y_{ik} = \gamma_0 + \gamma_1 T_k \times LowIncome_i + \gamma_2 T_k \times MiddleIncome_i + \gamma_3 T_k \times HighIncome_i \\ + \gamma_4 LowIncome_i + \gamma_5 HighIncome_i + \delta_{pk} + x'_{ik} + \epsilon_{ik} \end{aligned} \tag{2}$$

where $LowIncome_i$ is a dummy that equals one if household's total income at baseline lies in the first tercile of the distribution (corresponding to an average income of 1,123 Rs per

[21] We refer the reader to Table A5 in the Appendix for detailed descriptions of the outcome variables considered in our analysis.

[22] Since both baseline and endline were carried out in three waves, survey-round dummies account for waves' unobserved heterogeneity.

month in real terms); $MiddleIncome_i$ is a dummy that equals one if households' total baseline income lies in the second tercile (average income of 3,185 Rs a month in real terms); and $HighIncome_i$ is a dummy that equals one if households' total baseline income lies in the third tercile (average income of 10,707 Rs a month in real terms).

In light of the randomized design, the key assumption for causal identification is that treatment status is orthogonal to ϵ_{ik}. Table A1 presents balancing checks for our core household sample at baseline; overall, the treatment and control groups are balanced along the majority of observable characteristics discussed in section 3.1.1, suggesting that the randomisation was successfully implemented. Households in the treatment group are slightly smaller on average and slightly more likely to belong to the most backward caste. These differences are however quite small in magnitude. We account for these imbalances in our analysis by including these variables, measured at baseline, alongside a number of other socio-economic characteristics chosen by LASSO.

4 Results

4.1 Village-level treatment effects on Income and Poverty

To test the predictions outlined in Section 2.2, we first look at the impacts of the large KGFS capital injections in the village economy on income and poverty.

Column 1 of Table 2 reports average treatment effects on total monthly household income estimated on the sample of 14,360 households that includes both the core sample of 4,160 households and additional 10,200 observations from the village population census conducted in our service areas. Two years after the start of KGFS expansion, we find a 14% significant increase in household income compared with the control group. The treatment is also associated with a significantly lower share of poor households: -9% of a control group mean of 33%. Column 3-5 of Table 2 restrict the poverty analysis to the core sample. Results are fairly consistent with column 2: the probability of a household being poor at endline is 7.5% lower in the treatment group (Column 3). This result holds in significance and magnitude also when we restrict the analysis to households for which we collected information on monthly income both at baseline (BL) and endline (2,565 households, "BL Income" sample, Column 4). Restricting the analysis to the "BL Income" sample allows us to look at poverty dynamics – in particular, at households' transition out of poverty, which we measure as the probability that a household that was poor at baseline moved out of poverty at endline. Results are shown in Column 5: households in treated villages are +17.4% significantly more likely to have moved out of poverty at endline than households in control villages.

Taken together, results from Table 2 indicate that the expansion of KGFS succeeded in significantly reducing poverty in treated villages. But did access to formal financial services improve living conditions among even the poorest rural villagers, and how? In the next sections, household-level analysis of income, mental health and occupations is used alongside with heterogeneity analysis to cast light on the mechanisms behind our results.

4.2 Household-level impacts on Income, Wealth and Mental Health

We restrict our analysis to the core sample of 4,160 households and consider monthly income, wealth, mental health, borrowing and occupations to study the direct and indirect effects of rural banking expansion.

Table 3 shows average (Panel A and B) and heterogeneous (Panel C) treatment effects on household income, wealth and mental health. Average monthly income in the core sample, reported in Column 1, Panel A of Table 3 is 13% significantly larger in the treatment than in the control group (and 23% larger when we further restrict the sample to the "BL Income" household sample, Panel B). This result is very similar in magnitude to the treatment effects on household income shown in Column 1 of Table 2, indicating that the core sample is fairly representative of the broader village population.

We next consider household wealth, which is measured through a standardized index of households' durables, including land, electrical appliances like fans, smartphones, and cookers, and vehicles like bicycles, motorcycles and rickshaws.[23] Column 2, Panel A of Table 3 shows that the assets index is +0.03 standard deviation significantly higher in the treatment group – with similar results when we restrict the sample to households for which we have income information both at baseline and endline, Panel B. This result indicates that the expansion of KGFS led to positive impacts on treated villagers' wealth, as well.

Our third outcome of interest is mental health, which we measure combining individual levels of cortisol and DHEA[24] into a standardized index.[25] Treatment effects on women's psychological well-being, measured through this stress biomarkers index, are shown in Column 3, Panel A of Table 3. Women in treated villages have -0.07 standard deviation lower levels of stress than in control villages. We find a similar effect both in magnitude and significance when restricting the survey sample to households for which we have baseline income information. This result indicates that, even among a poor population that has limited experience with formal borrowing, the mental health benefits of borrowing outweigh potential negative

[23]The index is computed following Kling et al. (2007) by standardizing each asset category (subtracting the control group mean and dividing by the control group standard deviation), and aggregating them into a summary index defined to be the equally weighted average of these z-scores.

[24]We refer to section 3.1.1 for a discussion on how these samples were assayed.

[25]All endocrine parameters have been log-transformed to approach a normal distribution, as is standard practice in the scientific literature. In standardizing the stress index, we followed the same procedure described for the construction of the standardized index of households' assets: we first standardize each of the components (subtracting the control group mean and dividing by the control group standard deviation), and then aggregate them into a summary index defined to be the equally weighted average of these z-score, as in Kling et al., 2007.

impacts on stress of formal debt.[26] As a further robustness check, we estimate income treatment effects on the sample of households for which we obtained stress measurements (2,953 households). Results are shown in Column 4 of Table 3: the ITT coefficient is significant and slightly larger in magnitude than the the one reported in column 1. This finding further corroborates the existence of a positive link between poverty reduction and improvements in mental health.

We next look for variation in treatment effects according to baseline income levels. Results in Panel C of Table 3 show that the main effects on income are concentrated among poorest and wealthiest households, although the difference is not statistically significant at conventional levels. Heterogeneous effects on stress are also concentrated among the same segments of the village population that experienced the largest increase in income.

Taken together, results from Table 3 indicate a strong, positive impact of rural bank branch expansion on poverty and psychological well-being. Our analysis also reveals that better-off households experienced the bulk of income gains from increased availability of formal credit offered by bank branches.

4.3 Impact on Financial Access

The evidence on poverty reduction resulting from improved financial access may be either the result of direct effects of KGFS on borrowers' self-employment activities, or of indirect (spillover) effects whereby cheaper formal credit led to an expansion in the local economic activities with positive effects on borrowing and non-borrowing households, or both channels affecting different household segments.

[26] We estimate equation 1 and 2 also for DHEA and cortisol, separately, see Table A4. Results confirm that women living in treated villages experienced significantly lower long-term stressful conditions than women in control villages. We also identify a negative and significant median effect of -7% and -5% for DHEA and cortisol, results available upon request.

We use administrative data from KGFS on financial products' take up and self-reported financial information from households in the study sample to study whether the provision of credit by KGFS relaxed financial constraints, and for which segment of the population in the income spectrum.

Figure A1 shows KGFS take-up rates computed as the mean number of financial products (by category) disbursed by KGFS in treatment services areas in the first 18 months after the bank branch opening in each treated service area. These numbers are then weighted by each KGFS catchment area's relative population as per the 2011 Indian Census. Figure A1 shows that KGFS succeeded in achieving high take-up rates of its financial products in a relatively short time: in the first year and half since the opening of a KGSF bank branch, almost one in three households (27%) had already taken up the full suite of financial products offered by KGFS (loans, insurance and savings); this share reaches about 35% for loans only. Figure A1 also shows that loans and insurance policies are the most sold financial products by KGFS.[27] Overall, KGFS penetration strategy looks considerably successful, especially compared with Microfinance Institutions either in India or in other low-income countries such as Mexico or Morocco: in the evaluation of the expansion of Spandana Microfinance in urban Andra Pradesh, India, Banerjee et al. (2015) report 18% loan take-up rates fifteen to eighteen months after the introduction of the microfinance program. Similar take-up rates are observed in the microfinance evaluations in Morocco (Crépon et al., 2015) and Mexico (Angelucci et al., 2015). This may be also explained by the fact that a large share of the households had already access to financial products, and the entry of KGFS in the villages further accelerated the process of financial inclusion.

Survey data on households' financial information complement the evidence collected through

[27] One reason for lower take-up rates for savings product could be the fact that, at baseline, most of the study households (85%) already had a savings account. Among loans, JLG ones represent almost 90% of KGFS lending portfolio, followed by Personal Loans (2%), which are individual loans, and Emergency Loans (2%). Among insurance policies, personal-accident insurances are the most sold product (73%), followed by life insurance (26%) and livestock insurance products (1%). Data from KGFS Customer Management System.

administrative data on financial product take up. Results from estimating equation 1 on financial outcomes are shown in Table 4. Column 1, Panel A of Table 4 reports average treatment effects on households' overall formal financial inclusion, measured through a standardized index as in Kling et al. (2007), whose components include total formal borrowed amount (outstanding, in the last 24 months), the number of active insurance accounts and total formal saving amount, as well as the probability to have at least one formal outstanding loan, to have at least an active insurance account, and to have formal savings.[28] Formal financial inclusion is on average +0.05 standard deviations higher in treatment than in control villages, confirming that the expansion of KGFS has significantly improved treated villagers' access to formal financial products and services. Moreover, the estimated coefficient remains stable in significance and magnitude in Panel B for the income panel sample.

Column 2-6, Panel A and B of Table 4 show treatment effects on the extensive and intensive margin of formal and informal borrowing, respectively. Column 2 in particular indicates that treated households are 35% more likely to report a JLG loan at endline, confirming a strong first-stage of the studied intervention. Households in the treatment group are overall 9% more likely to have outstanding debt and they borrow 9% more credit than the control group from formal lending sources. By contrast, households' reliance on the informal lending sector reduced by 7% and 10% at the extensive and intensive margin, respectively.

All in all, Panel A and B of Table 4 indicate that treated villagers' reliance on informal, more expensive credit largely reduced two years after the start of KGFS expansion, and it was almost entirely compensated by increased borrowing from formal, and cheaper, lending sources, particularly JLG loans. Importantly, the increase in formal borrowing did not come at the expenses of increased overall indebtedness.

We then turn to the heterogeneous treatment effects of baseline poverty on formal and infor-

[28] We classify as formal lending sources: private banks, NGO/MFIs (e.g. Equitas, Gram Vidiyal, Smile, Mathura etc.), nationalized banks, PACs/Co-operative banks, self-help groups (SHGs), and non-banking financial corporations.

mal financial access in Panel C of Table 4. Formal financial inclusion and formal borrowing in particular have increased across the income spectrum. Column 5-6 of Panel B of Table 4 report heterogeneous treatment effects on informal borrowing. Better-off households drive the reduction in informal borrowing (Column 5 and 6).

4.3.1 Usage of Formal Loans

Taken together, results from Table 3 and Table 4 indicate that income increased across the population spectrum, and so did formal borrowing. Still, these effects may be driven by a direct impact of KGFS expansion, which contributed to relax financial constraints for the entire village population, or by a combination of both direct and indirect effects whereby better-off villagers were more directly affected by KGFS expansion through an increase in entrepreneurial activities, and these effects spilled over to poorer households.

The study of the usage of formal loans helps us disentangle across the two mechanisms. We distinguish among the following loan usage categories: farming and business investment; health expenditures; migrations costs; education expenditures; pay rent; repay old debt; house/land repairs or upgrade; jewlery purchase; wedding and other functions; day to day items (food, clothes, etc.) Panel A and Panel B of Table 5 show that treated villagers borrowed from formal lenders disproportionately more for farming and business activities: the ITT coefficient is positive and significant and in magnitude much larger than for the other outcomes. Panel C of Table 5 shows heterogeneous treatment effects across the income distribution: formal borrowing for productive activities is mostly concentrated among better-off households (Column 1). Conversely, households in the lowest income tercile used formal borrowing for education, weddings and other functions to a higher extent.

Results from Table 5 indicate that relatively better-off households used their formal loans for income-generating activities, while poorer households did less so. These findings are in line with the literature showing that less wealthy household do not use loans for investment (Lloyd-Ellis and Bernhardt, 2000; Ghatak et al., 2007).

4.4 Testing direct and indirect effects: Impact on Occupations and Employment

We next estimate treatment effects on agriculture and non-agriculture self-employment to study how the expansion of KGFS affected households' economic activities. We then study impacts on business outcomes and wages to assess economy-wide effects.

Panel A of Table 6 shows average treatment effects for the full study sample (n=4,160), while again Panel B restricts the analysis to the "BL Income" sample (n=2,570). Column 1 and 2, Panel A consider differences at endline in the probability households report having at least one member being self-employed in the agriculture and non-agriculture sector, respectively. We do observe a decrease in farming households (although the ITT coefficient is imprecisely estimated), and a significant increase in the likelihood that at least one member in treated households is self-employed in the non-agriculture sector (+7% of control group mean of 0.28). Consistent with a shift towards non-agricultural economic activities shown in column (1) and (2), column (3), Panel A of Table 6 shows a significant decrease in farming income in treated villages (-31%).[29]

Column 4-6 of Panel A and Panel B consider business outcomes. We find a significant expansion in self-employment both in terms of business sales (+20%), and the value of business equipment (+18%)[30]. Households in treated villages are also 33% more likely to

[29] Table A3 in the Appendix further corroborates results on farming income by showing negative treatment effects on farming profit and harvest yield, which are especially concentrated among wealthier households.

[30] Business equipment is measured as the total monetary value of inventory and equipment rented or purchased in the past 12 months for the business activity

employ individuals outside the household in the business activity (+0.01 of control mean of 0.03).

Panel C of Table 6 presents heterogeneous treatments effects on occupations and employment-related outcomes. Treatment effects appear concentrated among better-off households, who are significantly more likely to be self-employed outside agriculture, and are also more likely to report higher business sales and wealth; they are also significantly more likely to employ non-household members.

Results from Table 6, together with previous findings, indicate a clear, positive link between access to formal loans, poverty reduction and larger investments undertaken by wealthier villagers. Formal financial access has increased investment in and returns from self-employment by relaxing financial constraints for better-off households (direct effect), while also benefiting less entrepreneurial ones through increased labor opportunities (indirect effect).

To additionally test the existence of spillover effects, we estimate treatment effects on wages, both from our core sample and the village sample. Results are shown in Panel A of Table 7. While estimates on wages for the core sample appear noisy, we find a 6% significant increase in weekly wages for an additional sample of almost 2,300 households living in the same villages as the core sample, a result that once more speaks to an increase in labor demand.[31]

[31] In principle, changes in labor demand and in wages in response to changes in financial constraints could be either due to changes in the aggregate demand of goods and services or in investment in human capital. While this goes beyond the focus of our paper, we refer to Breza and Kinnan (2018) for a discussion on this. Questions on wages were administered only to our core household sample and to an additional sample of 2,300 households ('Mini' survey sample). Since the formulation of these questions was slightly different across surveys, we do not pool these samples together.

5 Conclusions

We report on a nine-year long, large-scale randomized controlled trial in Tamil Nadu that evaluates the impact of Kshetriya Grameen Financial Services (KGFS), an Indian private sector bank that offers rural formal financial products – mainly micro-credit – at fair terms. Two years from the start of KGFS' expansion, treated households earn 13%-14% higher income than control households, this result being consistent across the income distribution, and translating into a 8%-9% reduction in the share of households living below the poverty line in treated areas, as well as a -0.07 standard deviations significant reduction in chronic stress.

We hypothesise that our findings are driven by improved formal financial access relaxing financial constraints for better-off households, leading to larger investments, business expansion, and increased labor demand. Consistent with our hypothesis and with a model of credit constraints and entrepreneurship, we do find that households in treated villages are significantly more likely to be formally financially included, but also less reliant on informal lending sources.

Treated villagers are 7% more likely to report one member working in non-agriculture self-employment, at the end of the intervention. They also report higher business outcomes, both in terms of investment, sales and employment. We also detect a 6% average increase in total weekly wages, suggesting that the relaxation of financial constraints increases labor demand through general equilibrium effects.

Our findings show that the expansion of KGFS benefited the village population through the relaxation of financial constraints boosting self-employment and labor demand. This, in turn, has generated substantial income gains in the village economies. Our paper casts novel light on the mechanisms through which rural banking reduces aggregate poverty: access to formal finance improves household income without negative impacts on mental health.

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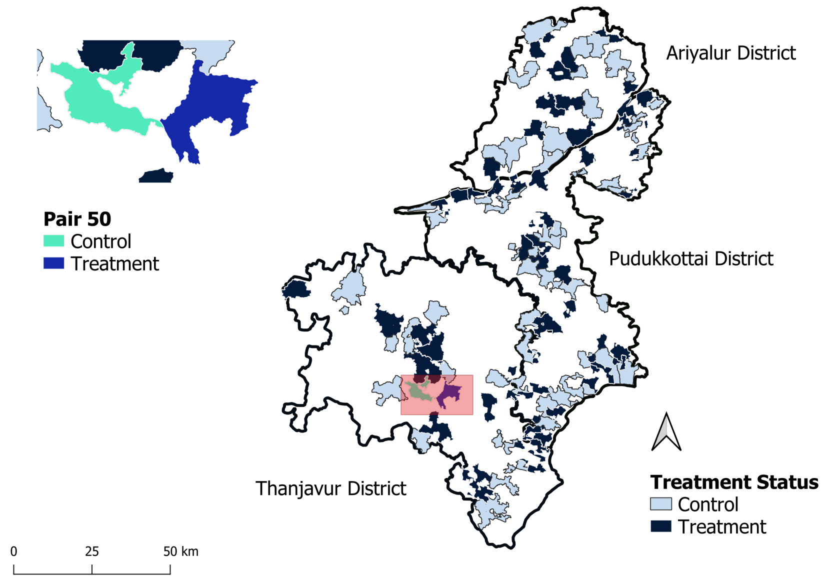
Figures and Tables

Figure 1: Service Areas of Study, by District



Note: This figure shows the geographical location of each of the 50 pairs of service areas under study over three districts in Tamil Nadu: Ariyalur, Pudukkottai and Thanjavur. The figure on the top left shows an example of a treatment and control service area belonging to the same pair (Pair 50, in this case).

Figure 2: Study Sample Diagram, Endline

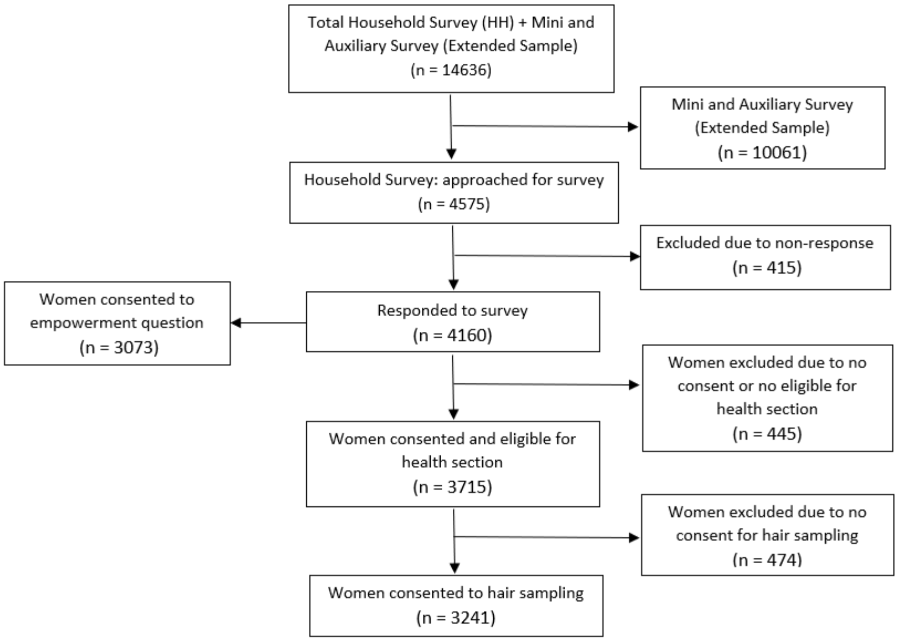


Table 2: Treatment Effects on Poverty Rates

	HH income	Poor	Poor	Poor	Poor to Rich
	(1)	(2)	(3)	(4)	(5)
Treated	0.14	-0.03	-0.03	-0.04	0.03
	(0.04)***	(0.01)***	(0.01)***	(0.01)**	(0.01)**
Sample	Census	Census	Household	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	8.21	0.33	0.40	0.39	0.39
N	14359	14359	4158	2565	2565

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Poor to Rich is a dummy that equals one if the household lived below the poverty line at baseline and moved out of poverty at endline. Rich to Poor is a dummy that equals one if the household lived above the poverty line at baseline and moved below the poverty line at endline. We have information on baseline income for 2,576 households from the core sample. All regressions include pair and survey round fixed effects. We include in the regression the best controls selected through lasso (OLS regression).

Table 3: Treatment Effects on Income, Wealth and Mental Health

	HH Income (log)	Asset Index	Stress Index	HH Income (log) (Stress Index Sample)
Panel A: Intention-To-Treat Effects				
	(1)	(2)	(3)	(4)
Treated	0.13	0.03	-0.07	0.15
	(0.05)**	(0.01)**	(0.02)***	(0.06)***
Sample	Household	Household	Household	Household
Control Dep Var Mean	8.16	0.00	0.00	8.32
N	4158	4159	2953	2952
Panel B: Intention-To-Treat Effects				
	(1)	(2)	(3)	(4)
Treated	0.23	0.03	-0.07	0.20
	(0.07)***	(0.01)***	(0.02)***	(0.08)***
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	8.15	0.00	0.08	8.32
N	2565	2566	1847	1846
Panel C: Heterogenous Treatment Effects				
	(1)	(2)	(3)	(4)
γ_1: Low Income at BL X Treated	0.27	0.05	-0.12	0.10
	(0.16)*	(0.02)**	(0.04)***	(0.16)
γ_2: Middle Income at BL X Treated	0.16	0.02	0.00	0.15
	(0.13)	(0.02)	(0.04)	(0.13)
γ_3: High Income at BL X Treated	0.28	0.04	-0.09	0.42
	(0.16)*	(0.03)	(0.05)*	(0.18)**
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean Low Income	7.62	-0.11	0.13	8.02
Control Dep Var Mean Middle Income	8.24	-0.01	0.05	8.38
Control Dep Var Mean High Income	8.58	0.13	0.06	8.53
N	2565	2566	1847	1846
$\gamma\_1 = \gamma\_2$ (P-value)	0.61	0.45	0.02	0.81
$\gamma\_1 = \gamma\_3$ (P-value)	0.97	0.82	0.56	0.24
$\gamma\_2 = \gamma\_3$ (P-value)	0.57	0.65	0.14	0.27

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Panel A includes the core household sample (n=4,160). Panel B includes the core sample for which we have income information at BL. The Sample in Column 3 and 4 includes only women that consented to hair sampling. In Panel A and B, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel C shows heterogeneity analysis based on core sample households' income levels at baseline, classified in terciles. We have information on baseline income for 2,565 households from the core sample. Asset Index (column 2) is the mean of standardized variables including all assets owned by a core sample household, following a similar approach as Kling, Liebman and Katz (2007). Stress Index (Column 4) is a standardized index of DHEA and cortisol, following a similar approach as Kling, Liebman and Katz (2007). Household income has been top-coded, 3 standard deviations from the mean before taking the log. All regressions include pair and survey round fixed effects. We include in the regression the best controls selected through lasso (OLS regression).

Table 4: Treatment Effects on Take up of Financial Products

	Formal Financial Inclusion	Has JLG Loan	Has Formal Oustanding Loans	Total Formal Borrowing (Outstanding)	Has Informal Oustanding Loans	Total Informal Borrowing (Outstanding)
Panel A: Intention-To-Treat Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.05	0.11	0.06	4446.61	-0.04	-3963.66
	(0.01)***	(0.01)***	(0.01)***	(2067.69)**	(0.01)***	(1756.69)**
Sample	Household	Household	Household	Household	Household	Household
Control Dep Var Mean	0.00	0.31	0.66	51810.50	0.61	38089.56
N	4138	4159	4158	4146	4158	4146
Panel B: Intention-To-Treat Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.04	0.12	0.05	5282.28	-0.04	-5334.79
	(0.02)**	(0.02)***	(0.01)***	(2452.54)**	(0.01)***	(2363.71)**
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	0.03	0.32	0.70	56095.77	0.61	40169.05
N	2559	2566	2565	2560	2565	2560
Panel C: Heterogeneous Treatment Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
γ_1: Low Income at BL X Treated	0.04	0.14	0.07	5924.82	0.03	-2644.47
	(0.03)	(0.03)***	(0.03)**	(4018.12)	(0.03)	(4218.02)
γ_2: Middle Income at BL X Treated	0.03	0.10	0.03	3075.99	-0.07	-8277.73
	(0.03)	(0.03)***	(0.02)	(5122.42)	(0.03)**	(4181.31)**
γ_3: High Income at BL X Treated	0.04	0.13	0.06	6568.88	-0.07	-4081.08
	(0.03)	(0.03)***	(0.03)**	(6308.25)	(0.03)***	(4179.11)
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean Low Income	-0.10	0.25	0.64	45726.05	0.59	36837.21
Control Dep Var Mean Middle Income	0.00	0.35	0.71	50005.65	0.65	40870.44
Control Dep Var Mean High Income	0.20	0.36	0.76	73444.76	0.59	42731.20
N	2559	2566	2565	2560	2565	2560
$\gamma\_1 = \gamma\_2$ (P-value)	0.69	0.46	0.40	0.68	0.03	0.38
$\gamma\_1 = \gamma\_3$ (P-value)	0.94	0.83	0.84	0.94	0.03	0.81
$\gamma\_2 = \gamma\_3$ (P-value)	0.78	0.56	0.50	0.69	1.00	0.45

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Panel A includes the core household sample (n=4,160). Panel B includes the core sample for which we have income information at BL. In Panel A and B, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel C shows heterogeneity analysis based on core sample households' income levels at baseline, classified in terciles. We have information on baseline income for 2,565 households from the core sample. Formal financial inclusion index is the mean of standardized variables including total formal borrowed amount (outstanding, last 24 months), the number of active insurance accounts, total formal saving amount, and the probability the household has any formal outstanding loan, any active insurance, and any formal savings account. The index is constructed following a similar approach as Kling, Liebman and Katz (2007). All regressions include pair and survey round fixed effects. A loan is defined as formal if it is taken from a: private bank, NGO/MFI, nationalized bank, PAC/co-operative bank, SHG, non-banking financial corporation. We classify as informal lending sources: friends, neighbor, relative, shopkeeper, employer, moneylender, pawn broker, landlord, rotating savings group (ROSCA) or other savings group, Chitfund, and Financiers, Religious Trusts (e.g. Panchayat Kovil Trust). Formal and Informal borrowing amounts have been top-coded, 3 standard deviations from the mean. We include in the regression the best controls selected through lasso (OLS regression).

Table 5: Treatment Effects on Usage of Formal Loans

	Farming/Business Investment	House/Land Repairs or Upgrade	Health	Education	Migration Costs	Repay Old Debt	Rent	Jewelry Purchase	Weddings or Functions	Day to Day items
Panel A: Intention-To-Treat Effects										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	3401.54	819.19	359.57	-59.71	-58.79	461.61	-11.50	251.93	-210.34	197.32
	(1291.67)***	(876.42)	(175.79)**	(270.83)	(152.82)	(117.22)***	(3.47)***	(75.46)***	(434.73)	(180.68)
Sample	Household	Household	Household	Household	Household	Household	Household	Household	Household	Household
Control Dep Var Mean	12862.09	16713.80	1585.28	3368.47	1141.14	1081.83	12.94	477.01	4497.61	3382.76
N	4146	4146	4146	4146	4146	4146	4146	4146	4146	4146
Panel B: Intention-To-Treat Effects										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	4679.01	397.40	182.25	-131.33	11.73	366.23	-2.41	111.36	-194.49	98.75
	(1722.38)***	(1194.57)	(218.76)	(278.33)	(212.58)	(132.97)***	(2.32)	(64.36)*	(572.77)	(241.31)
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	13995.86	19186.06	1509.96	3097.94	1163.02	777.28	3.52	499.02	4892.48	3594.93
N	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560
Panel C: Heterogeneous Treatment Effects										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
γ_1: Low Income at BL X Treated	3272.98	2026.72	-582.60	1095.85	-16.42	433.25	-9.89	173.13	708.18	131.38
	(2290.83)	(2381.42)	(470.83)	(669.46)	(313.20)	(313.63)	(8.88)	(170.08)	(1040.36)	(528.79)
γ_2: Middle Income at BL X Treated	6682.02	-1290.01	27.26	-99.20	207.46	39.29	1.78	-38.57	-700.19	151.78
	(2704.92)**	(2661.83)	(528.83)	(629.85)	(537.91)	(312.44)	(2.90)	(184.10)	(1022.75)	(444.42)
γ_3: High Income at BL X Treated	3967.84	750.59	1173.52	-1265.89	-78.46	657.87	0.68	213.37	-537.87	110.22
	(3836.45)	(3103.98)	(609.89)*	(785.39)	(548.46)	(316.90)**	(1.69)	(205.96)	(1051.28)	(550.89)
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean Low Income	10663.49	15132.85	1707.58	1861.24	504.45	694.29	10.93	398.41	4028.55	2970.14
Control Dep Var Mean Middle Income	10619.07	16664.98	1505.92	2891.79	1128.30	761.91	0.00	607.09	5438.67	3496.01
Control Dep Var Mean High Income	21168.89	26122.33	1314.93	4579.42	1867.32	878.42	0.00	478.79	5149.22	4337.51
N	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560
γ_1 = γ_2 (P-value)	0.33	0.39	0.43	0.21	0.73	0.39	0.29	0.43	0.36	0.98
γ_1 = γ_3 (P-value)	0.88	0.76	0.03	0.04	0.93	0.67	0.28	0.90	0.39	0.98
γ_2 = γ_3 (P-value)	0.57	0.67	0.23	0.32	0.74	0.22	0.42	0.44	0.91	0.96

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Panel A includes the core household sample (n=4,160). Panel B includes the core sample for which we have income information at BL. In Panel A and B, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel C shows heterogeneity analysis based on core sample households' income levels at baseline, classified in terciles. We have information on baseline income for 2,565 households from the core sample. We include in the regression the best controls selected through lasso (OLS regression).

Table 6: Treatment Effects on Occupations and Employment

	Agri Self-Emp	Non-Agri Self-Emp	Total farming income	Log Sales Self-Emp (30 days)	Log value of equipment rented or purchased (last 12 months)	Employs non-HH members
Panel A: Intention-To-Treat Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.01	0.02	-0.31	0.20	0.18	0.01
	(0.01)	(0.01)**	(0.14)**	(0.07)***	(0.05)***	(0.00)**
Sample	Household	Household	Household	Household	Household	Household
Control Dep Var Mean	0.44	0.28	3.23	1.24	0.74	0.03
N	4155	4145	4158	4142	4147	4154
Panel B: Intention-To-Treat Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.02	0.03	-0.48	0.29	0.29	0.00
	(0.02)	(0.01)***	(0.18)***	(0.08)***	(0.06)***	(0.00)
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	0.47	0.26	3.55	1.16	0.67	0.03
N	2563	2554	2565	2554	2554	2563
Panel C: Heterogeneous Treatment Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
γ_1: Low Income at BL X Treated	-0.00	-0.01	-0.17	0.13	0.17	-0.00
	(0.02)	(0.03)	(0.28)	(0.15)	(0.11)	(0.01)
γ_2: Middle Income at BL X Treated	-0.03	0.04	-0.64	0.44	0.27	-0.00
	(0.03)	(0.03)	(0.28)**	(0.15)***	(0.12)**	(0.01)
γ_3: High Income at BL X Treated	-0.04	0.07	-0.60	0.31	0.42	0.02
	(0.02)*	(0.03)**	(0.29)**	(0.23)	(0.16)***	(0.01)*
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean Low Income	0.50	0.24	3.77	0.61	0.35	0.02
Control Dep Var Mean Middle Income	0.43	0.24	3.28	1.00	0.62	0.02
Control Dep Var Mean High Income	0.49	0.29	3.63	1.91	1.04	0.05
N	2563	2554	2565	2554	2554	2563
γ_1 = γ_2 (P-value)	0.53	0.37	0.19	0.17	0.58	0.80
γ_1 = γ_3 (P-value)	0.25	0.11	0.27	0.54	0.25	0.16
γ_2 = γ_3 (P-value)	0.65	0.50	0.91	0.68	0.49	0.15

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Panel A includes the core household sample (n=4,160). Panel B includes the core sample for which we have income information at BL. In Panel A and B, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel C shows heterogeneity analysis based on core sample households' income levels at baseline, classified in terciles. We have information on baseline income for 2,565 households from the core sample. All outcomes are measured using endline data. Sales from self-employment or business include estimated value of sales of finished goods over the most recent 30 days. Business wealth is the value of equipment and inventory in the business. All regressions include pair and survey round fixed effects. We include in the regression the best controls selected through lasso (OLS regression).

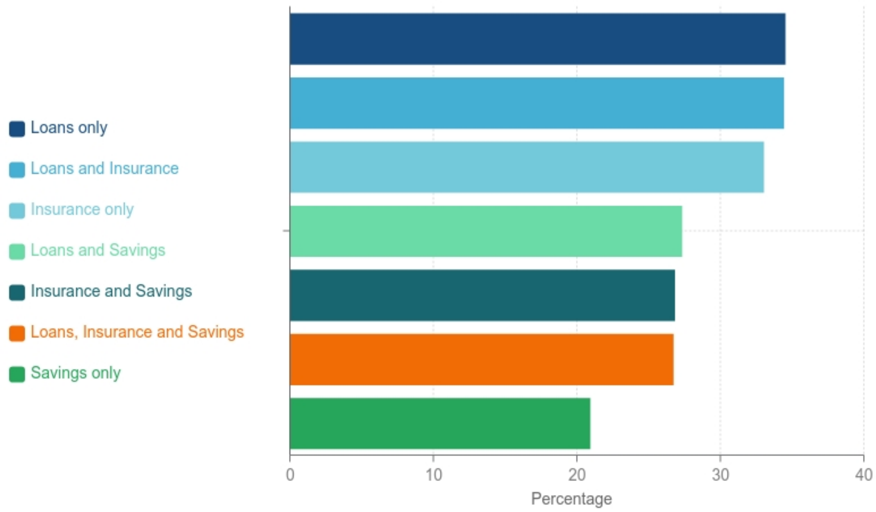
Table 7: Treatment Effects on Wages

	Log Wage Labor Income (daily)	Log Wage Labor Income (weekly)	Log Total Weekly Wages
Panel A: Intention-To-Treat Effects			
	(1)	(2)	(3)
Treated	0.04	0.06	0.06
	(0.06)	(0.08)	(0.03)**
Sample	Household	Household	Auxiliary
Control Dep Var Mean	3.52	4.35	0.33
N	4160	4160	2293
Panel B: Intention-To-Treat Effects			
	(1)	(2)	
Treated	0.08	0.09	
	(0.09)	(0.11)	
Sample	Household (BL Income)	Household (BL Income)	
Control Dep Var Mean	3.52	4.35	
N	2567	2567	
Panel C: Heterogeneous Treatment Effects			
	(1)	(2)	
γ_1: Low Income at BL X Treated	0.31	0.40	
	(0.17)*	(0.22)*	
γ_2: Middle Income at BL X Treated	0.03	0.02	
	(0.18)	(0.22)	
γ_3: High Income at BL X Treated	-0.05	-0.04	
	(0.23)	(0.29)	
Sample	Household (BL Income)	Household (BL Income)	
Control Dep Var Mean Low Income	3.01	3.69	
Control Dep Var Mean Middle Income	3.79	4.69	
Control Dep Var Mean High Income	3.74	4.62	
N	2567	2567	
$\gamma\_1 = \gamma\_2$ (P-value)	0.31	0.28	
$\gamma\_1 = \gamma\_3$ (P-value)	0.27	0.29	
$\gamma\_2 = \gamma\_3$ (P-value)	0.78	0.87	

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Panel A includes the core household sample (n=4,160). Panel B includes the core sample for which we have income information at BL. In Panel A and B, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel C shows heterogeneity analysis based on core sample households' income levels at baseline, classified in terciles. Wages from non-household employment include cash wage and cash value of in-kind compensation. All regressions include pair and survey round fixed effects. We include in the regression the best controls selected through lasso (OLS regression).

6 Appendix

Figure A1: KGFS Penetration Rates in Treated Service Areas



Notes: The graph provides an overview of the penetration rate for each product when the bank opened for 18 months. KGFS provides the following bank products: Loans, Insurance, Savings, Investment, Remittance, and Utility Payment. The figure shows take-up rate for the major products which are loans, insurance, and savings.

Table A1: Baseline Balance Checks

	Control Mean [SD]	**Coefficient** difference (SE)	**N**
	[1]	[2]	[3]
Panel A: Demographics			
Household Head is Male	0.73	-0.01	4066
	[0.44]	(0.02)	
Years of Education of Household Head	7.46	0.04	4066
	[4.70]	(0.22)	
Number of Household Members	4.60	-0.14***	4066
	[1.91]	(0.07)	
Most Backward Caste / Scheduled Caste and Tribe	0.56	0.04***	4066
	[0.50]	(0.04)	
Household Owns Land	0.55	-0.00	4064
	[0.50]	(0.04)	
Panel B: Income, Consumption and Poverty			
Per capita HH Income (30-day), topcoded 3sd	1505.81	126.38	2727
	[2171.98]	(164.94)	
Below Poverty Line (Income, World Bank Headcount Ratio)	0.55	-0.00	2725
	[0.50]	(0.03)	
Per capita HH Consumption (30-day), topcoded 3sd	767.87	-4.91	4063
	[550.50]	(36.27)	
Panel C: Borrowing, Saving, and Insurance Outcomes			
Household has Outstanding Formal Loans	0.55	0.01	4052
	[0.50]	(0.02)	
Household has Outstanding Informal Loans	0.72	-0.02	4052
	[0.45]	(0.02)	
Household Has Active Insurance	0.80	0.01	4066
	[0.40]	(0.02)	
Tot. Savings Amt (Rs)	4420.45	202.56	3960
	[9385.70]	(410.41)	
Share Informal Loans over Tot. Outstanding Loans	0.48	-0.01	3805
	[0.43]	(0.02)	
Panel D: Occupations, Employment, and Wages			
At Least 1 HH Member Works in Agricultural	0.62	-0.01	4066
	[0.48]	(0.03)	
At Least 1 Household Member is Self-Employed	0.17	-0.00	4063
	[0.37]	(0.01)	
Sales from Self-Employment or Business (30d), topcoded 3sd	2030.37	-33.37	4017
	[9317.94]	(361.57)	
Total Weekly Wages for Non-Household Employment	848.77	-3.59	4066
	[1903.11]	(83.57)	

Note : ***(**)(*) indicates significance at the 1%(5%)(10%) level. Panel A to panel D refer to the baseline household survey data, as conducted on the main study sample. Column [1] reports control group means, with standard deviations in parentheses. Column [2] reports the OLS coefficient estimates associated with regressing each outcome on a dummy indicating treatment. Pair fixed effects are included. Standard errors are clustered at the service area level. Column [3] reports the number of observations. Outcomes for which there are less than 3000 observations were collected only in later rounds of the survey, and hence are missing values from earlier survey rounds. All Rs. values are top-coded three standard deviations from the mean, unless otherwise specified. Trimmed variables are trimmed at three standard deviations from the mean. Pair 8 is dropped because of the branch location change.

Table A2: Analysis of Attrition Rates

	Control Mean [SD]	**Coefficient** difference (SE)	**N**
	[1]	[2]	[3]
The HH was surveyed at BL but was not surveyed at EL	0.058	-0.008 (0.005)	4684
The HH was not surveyed at BL but was surveyed at EL	0.035	0.000 (0.003)	4684

Note : ***(**)(*) indicates significance at the 1%(5%)(10%) level. Analysis conducted on the main study sample. Column [1] reports control group means, with standard deviations in parentheses. Column [2] reports the OLS coefficient estimates associated with regressing each outcome on a dummy indicating treatment. Pair fixed effects are included. Standard errors are clustered at the service area level. Column [3] reports the number of observations. Pair 8 is dropped because of the branch location change.

Table A3: Treatment Effects on Farming Outcomes

	Log Farming Profit	Harvest yield	Hires Labor
Panel A: Intention-To-Treat Effects			
	(1)	(2)	(3)
Treated	-0.36	-0.31	-0.02
	(0.13)***	(0.14)**	(0.01)
Sample	Household	Household	Household
Control Dep Var Mean	2.27	3.23	0.34
N	3438	4160	4160
Panel B: Intention-To-Treat Effects			
	(1)	(2)	(3)
Treated	-0.57	-0.47	-0.03
	(0.17)***	(0.18)***	(0.02)*
Panel	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	2.54	3.55	0.36
N	2089	2567	2567
Panel C: Heterogeneous Treatment Effects			
	(1)	(2)	(3)
γ_1: Low Income at BL X Treated	-0.41	-0.17	-0.02
	(0.25)	(0.28)	(0.03)
γ_2: Middle Income at BL X Treated	-0.74	-0.64	-0.05
	(0.27)***	(0.28)**	(0.03)
γ_3: High Income at BL X Treated	-0.50	-0.58	-0.03
	(0.26)*	(0.29)**	(0.03)
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean Low Income	2.59	3.77	0.39
Control Dep Var Mean Middle Income	2.34	3.28	0.34
Control Dep Var Mean High Income	2.72	3.62	0.37
N	2089	2567	2567
$\gamma\_1 = \gamma\_2$ (P-value)	0.36	0.20	0.42
$\gamma\_1 = \gamma\_3$ (P-value)	0.80	0.30	0.70
$\gamma\_2 = \gamma\_3$ (P-value)	0.48	0.87	0.70

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Panel A includes the core household sample (n=4,160). Panel B includes the core sample for which we have income information at BL. In Panel A and B, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel C shows heterogeneity analysis based on core sample households' income levels at baseline, classified in terciles.We have information on baseline income for 2,565 households from the core sample. All outcomes are measured using endline data. All regressions include pair and survey round fixed effects. We include in the regression the best controls selected through lasso (OLS regression).

Table A4: Treatment Effects on Mental Health

	Stress Index	Stress Index (DHEA non missing)	DHEA (log pg/mg)	Cortisol (log pg/mg)	Cortisol (log pg/mg), DHEA non missing
Panel A: Average Treatment Effects					
	(1)	(2)	(3)	(4)	(5)
Treated	-0.07	-0.07	-0.17	-0.03	-0.04
	(0.02)***	(0.03)***	(0.08)**	(0.02)	(0.02)
Sample	Household	Household	Household	Household	Household
Control Dep Var Mean	0.00	0.00	0.86	1.93	2.09
N	2953	2091	2091	2952	2090
Panel B: Intention-To-Treat Effects					
	(1)	(2)	(3)	(4)	(5)
Treated	-0.07	-0.07	-0.17	-0.04	-0.04
	(0.02)***	(0.03)**	(0.11)	(0.02)**	(0.02)*
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean	0.08	0.12	1.05	1.97	2.20
N	1847	1243	1243	1847	1243
Panel C: Heterogeneous Treatment Effects					
	(1)	(2)	(3)	(4)	(5)
γ_1: Low Income at BL X Treated	-0.12	-0.16	-0.45	-0.06	-0.09
	(0.04)***	(0.06)***	(0.17)***	(0.05)	(0.06)
γ_2: Middle Income at BL X Treated	0.00	0.03	0.11	-0.00	0.01
	(0.04)	(0.05)	(0.14)	(0.04)	(0.04)
γ_3: High Income at BL X Treated	-0.09	-0.09	-0.22	-0.07	-0.06
	(0.05)*	(0.06)	(0.27)	(0.04)*	(0.04)
Sample	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)	Household (BL Income)
Control Dep Var Mean Low Income	0.13	0.23	1.30	1.96	2.26
Control Dep Var Mean Middle Income	0.05	0.08	0.94	1.96	2.17
Control Dep Var Mean High Income	0.06	0.09	0.98	1.97	2.18
N	1847	1243	1243	1847	1243
$\gamma\_1 = \gamma\_2$ (P-value)	0.02	0.02	0.02	0.31	0.19
$\gamma\_1 = \gamma\_3$ (P-value)	0.56	0.43	0.50	0.89	0.70
$\gamma\_2 = \gamma\_3$ (P-value)	0.13	0.13	0.30	0.21	0.30

Note: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. In Panel A, OLS estimates (standard errors) are reported from regressing each dependent variable on a dummy indicating whether the household resides in a treated service area. Panel B shows heterogeneity analysis based on core sample households' consumption levels at baseline, classified in terciles where Tercile 1 indicates poorest households and Tercile 3 indicates wealthiest households. All regressions include pair and survey round fixed effects. We include in the regression the best controls selected through lasso (OLS regression).

Table A5: Variable Definitions for Income and Poverty

Variable	Definition
Log Household Income (Household Sample, and Census Sample)	Log of total self-reported household income over the last 30 days at endline, which is expressed in Indian Rupees and top-coded at 3 standard deviations from the mean.
Below Poverty Line (Income) (Household Sample, and Census Sample)	Dummy variable equal to 1 if the household's self-reported income per day per captica falls below 1.90 USD using the World Bank Poverty Line. 3 components: (1) Self-reported household income (2) Number of household members. (3) World Bank poverty line of USD 1.90 per day per capita (PPP 2011), converted in Indian Rupees for 2010 using PPP Rates from ICP - World Bank.
Asset Index	The index is the mean of several standardized variables. These variables include the number of the following asset that the household own (exclude government given asset): landline, cellphone, bicycle, motorcycle, car, rickshaw, cooker, radio, iron, fan, and furniture, following a similar approach as Kling, Liebman and Katz (2007).

Note: These variables are used in Table 1 and 2.

Table A6: Variable Definitions for Financial Inclusion

Variable	Definition
Formal Financial Inclusion Index	The index is the mean of several standardized variables. These variables include the number of active insurance accounts, total formal saving amount, and total formal borrowed amount (outstanding, last 24 months), the probability to have an active insurance, the probability to have a formal loan and the probability to have a formal saving account. The index is constructed following a similar approach as Kling, Liebman and Katz (2007).
Total Formal/Informal Borrowed Amount (Outstanding), Probability the household has at least a Formal/Informal loan	A loan is defined as formal if it is taken from a: private bank, NGO/MFI, nationalized bank, PAC/cooperative bank, SHG, non-banking financial corporation. A loan is defined as informal if it is taken from a: friend/neighbor/relative, shopkeeper, employer, moneylender, pawnbroker, landlord, ROSCA, chitfund, financier, or religious trust. These variables are the outstanding loans that are taken over the last 24 months and not yet repaid. Variables are Rupees amount and top coded at 3 standard deviations from the mean.

Note: These variables are used in Table 3.

Table A7: Variable Definitions for Employment and Occupations

Variable	Definition
Any Non-Agricultural	Dummy variable equal to 1 if at least one 1 household member works in any non-agricultural wage labor which includes non-farm labor (skilled), NREGA work, private formal salary job, government job, electrician, driver, woodworker, or household is self-employed in non-agricultural business.
Agricultural Only	Dummy variable equal to 1 if household works in only any agricultural wage labor and not work in any non-agricultural wage labor.
Sales from Self-Employment or Business (30 days)	This variable includes estimated value of sales of finished goods over the most recent 30 days. The values are expressed in Indian Rupees, and are top coded, or top coded and trimmed at 3 standard deviations from the mean.
Total Daily Wages (household sample)	The daily wages are calculated using total wages paid (hourly, daily, weekly, monthly, quarterly, half year, annually, or seasonally) to each household member who works for wage labor, and then converted all amount to daily wages. Total daily wages include cash wage and cash value of in-kind compensation and the amounts are aggregated to household level, expressed in Indian Rupees, and are top coded, or top coded and trimmed at 3 standard deviations from the mean.
Total Daily Wages (Mini sample)	Total wages across all labors of average monthly earnings at household level, and divided by 20 working days to calculate the daily wages. Amounts are expressed in Indian Rupees, and are top coded, or top coded and trimmed at 3 standard deviations from the mean.

Note: These variables are used in Table 5 and 6.

Table A8: Variable Definitions for Baseline Descriptive Variables

Variable	Definition
Demographics	
Head of Household Characteristics	Gender, years of education.
Household Characteristics	Number of Household Members, dummy variable equal to 1 if household belongs to most backwards caste, dummy variable equal to 1 if household belongs to scheduled caste and tribe, dummy variable equal to 1 if household own land
Income, Consumption and Poverty	
Total Household Consumption	Total household consumption includes consumption of food items (basic goods, meat and fish), temptation goods (alcohol, tobacco, sweet products, meal and beverage taken outside of home), education and religion expenditure. Recall period are harmonized at 30 days. Amounts are expressed in Indian Rupees and top coded and trimmed at 3 standard deviations from the mean.
Total Household Income	Self-reported household income: "How much rupees, in total, did household members earn in the last 30 days from all income-generating activities?" There are few observations in the table because household income was not collected in Baseline I. Amounts are expressed in Indian Rupees and top coded and trimmed at 3 standard deviations from the mean.
Below Poverty Line (using Income or Consumption)	Dummy variable equal to 1 if the household's self-reported income or consumption per day per captica falls below 1.90 USD using the World Bank Poverty Line. 3 components: (1) Self-reported household income or total household consumption. (2) Number of household members. (3) World Bank poverty line of USD 1.90 per day per capita (PPP 2011), converted in Indian Rupees for 2010 using PPP Rates from ICP - World Bank.

Table A8: Variable Definitions for Baseline Descriptive Variables (continue)

Variable	Definition
Borrowing, Savings and Insurance	
Household has Outstanding Formal/Informal Loans(s)	Dummy variable equal to 1 if household has outstanding formal or informal loans. A loan is defined as formal if it is taken from a: private bank, NGO/MFI, nationalized bank, PAC/co-operative bank, SHG, non-banking financial corporation. A loan is defined as informal if it is taken from a: friend/neighbor/relative, shopkeeper, employer, moneylender, pawnbroker, landlord, ROSCA, chitfund, financier, or religious trust. These variables are the outstanding loans that are taken over the last 24 months and not yet repaid.
Household has Active Insurance	Dummy equal to 1 if household has any active insurance account.
Total Savings Amount (Rupees)	Total savings amount that household has. Expressed in Indian Rupees and top coded at 3 standard deviations from the mean.
Informal Share of Total Outstanding Ratio	Total informal outstanding loans amount divide the sum of formal and informal outstanding loans amount. All the loan amounts are expressed in Indian Rupees.
Occupations, Employment, and Wages	
At Least 1 Household Members is Self-employed	Dummy variable equal to 1 if the household answered yes to question: "Is there any member of the household currently self-employed or the owner of a business of a business which excludes any sort of farming or animal-husbandry?"
At Least 1 Household Members Employed in Wage Labor	Dummy varaible equal to 1 if at least 1 household members employed in wage labor.
Total Daily Wages for Non-Household Employment , Sales from Self-Employment or Business	Please see variable definition for employment and occupation table.

Note: These variables are used in table 5 for baseline balance check.