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

Giorgia Barboni
Warwick University

Erica Field
Duke University

Rohini Pande
Yale University

Abstract

We evaluate how entry of a formal financial institution alters household well-being and economic activity in a village economy, using an at-scale experiment that randomized bank branch placement over 870 villages. Administrative data show that, within two years of branch opening, one in three households in banked villages had taken a formal loan and roughly a quarter had additionally taken up an insurance or savings product. Survey data show a corresponding 10% reduction in informal borrowing levels. Relative to control villages, poverty rates in treatment villages are 8%-9% lower and we observe significant reductions in biomarker-based psychological stress measures. Changes in the financial environment increase occupational diversification and economic activity: households in banked villages are 6% more likely to have a member working outside of agriculture, have 21% higher business income, and 6% higher wage income. Our evidence is consistent with a model of entrepreneurship in which access to cheaper formal credit relaxed financial constraints for better-off households and increased village-wide labor demand.

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1 Introduction

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). Motivated by this, in the last decades several governments have launched financial-inclusion initiatives in under-served areas. Although some of these programs have been associated with reductions in poverty (Burgess and Pande, 2005; Bruhn and Love, 2014; Célerier and Matray, 2019), a number of recent experimental studies show no average impact of microfinance on household income and poverty (Banerjee et al., 2015; Angelucci et al., 2015; Meager, 2019). These conflicting sets of empirical findings raise important questions regarding the circumstances under which reducing credit constraints improves the lives of the poor.

In this paper, we provide insight into this fundamental debate in the literature by evaluating the randomized roll-out of 50 brick-and-mortar microfinance bank branches across almost 900 rural villages in South India. Our experiment randomized the placement of branches across pairs of potential service areas identified by our partner bank. Each service area encompassed 5-12 villages that were unbanked at study onset. Leveraging two extensive socioeconomic surveys and biomarker measurements conducted on a sample of 4,160 households, we evaluate the impact of access to banking services on poverty, income and psychological wellbeing.

Two years after branch opening, households in treatment villages report 13%-14% higher monthly income and an increase in asset ownership of +0.03 standard deviations relative to control households. Moreover, we find that improved access to finance is associated with a significant long-term reduction in an index of stress biomarkers assayed from hair samples. This finding is possibly the first rigorous evidence that, even among 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.

Perhaps most striking of all, we observe an 8%-9% lower rate of poverty in treated compared to control villages 2-3 years after branch opening, indicating substantial welfare gains to relatively poor households of banking services in rural areas.[1] This is surprising in part because financial services provided through the private sector are normally directed disproportionately towards households that are relatively well-off. Moreover, households in the lowest tercile of the income distribution, who are primarily agricultural wage laborers in rural areas, are unlikely to be positioned to gain from entrepreneurial loans, as has been shown in the literature (Banerjee et al., 2019; Lloyd-Ellis and Bernhardt, 2000; Ghatak et al., 2007). Indeed, our partner lender offered standard "entrepreneurial" group loans designed to bolster investment among profitable microenterpreneurs. Although borrowing increased among households in the lowest income tercile, these loans were used primarily to finance consumption rather than investment.

However, it is still possible for banking services to benefit the poor (and thereby lower poverty) if relaxing credit constraints for higher income entrepreneurial borrowers leads to an expansion in local economic activity with spillover effects on job opportunities for lower income households. This prediction is in line with standard models of credit and entrepreneurship (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 more firmly establish 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

[1] 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.

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 inventory and business sales in treated villages are 25% and 21% 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, we find significantly higher agricultural wages in treated villages, which also indicates that reduced liquidity constraints in the village economy increased local labor demand.

Meanwhile, although we also observe an increase in formal borrowing among poorer households, their loans are used for consumption and education rather than in business. This suggests that the reduction in poverty we observe among poorer households is not driven by more profitable household businesses. Instead, poverty falls among the lowest income tercile by way of a large and significant increase in household wage income, consistent with the spillovers story. 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 evidence that rural banks can reduce poverty through both direct and indirect effects. They enable better-off households to shift out of the agricultural sector and invest in microenterprises, and thereby generate a "trickle-down" effect onto poorer households through higher labor demand both inside and outside of agriculture.

All in all, these findings demonstrate a clear causal impact of access to credit on economic growth, and provides novel evidence that liquidity constraints contribute to rural poverty. These results also constitute the first experimental evidence that banking services can reduce poverty. Although the finding corroborates quasi-experimental evidence from social banking policies (Burgess and Pande, 2005; Kaboski and Townsend, 2012; Bruhn and Love, 2014) , they depart from previous experimental estimates in the literature, which show null effects of banking services (Banerjee et al., 2015; Angelucci et al., 2015). There are two likely reasons for this. First, the bulk of those measure the impact of expanded banking services in urban settings where alternative financial products are readily available. Among the rural poor, financial constraints are likely to be considerably more binding. Second, existing experimental studies focus only on direct treatment impacts. In contrast, a key aspect of our study is the economy-wide nature of our intervention, which allows us to capture general equilibrium effects.[2]

Finally, this study provides the first rigorous evaluation of the mental health effects of formal debt, a major source of policy debate in many settings and one that is particularly pertinent to developing countries since the poor are more likely to face mental-health problems (Mullainathan and Shafir, 2013; Schilbach et al., 2016). This was accomplished through the collection of hair samples from more than 3,000 subjects, one of the largest empirical analyses of sex-hormone data in any setting and one of the only ones in a developing country context. 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). 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 a anxiety-inducing. This would be particularly likely if bank access leads to over-borrowing, reputation concerns or social pressure to repay, as

[2] In this sense, our approach is closer in spirit to the nonexperimental evaluation of microcredit impacts by Breza and Kinnan (2018), who analyze the impact of the microfinance crisis in Andra Pradesh on village-level wages, and find similar evidence on the positive relationship between credit provision and wages.

have been documented in other settings. Our results reveal that, in fact, banks can reduce poverty in underserved areas without significant negative effects on mental health.

2 Context and Methods

2.1 KGFS rural banking model

Our banking partner in this study was Kshetriya Grameen Financial Services (KGFS), a private-sector microfinance institution that provides credit through village bank branches.[3] KGFS is a fairly typical MFI that focuses on improving financial access among the rural poor. It follows an inclusive approach whereby no specific population segment is targeted, and no specific eligibility requirement exists for prospective customers.[4]

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

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

[4]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.

of village banking which grew its business profitably in almost all branch units over the course of our study.

2.2 Experimental Design and Study Sample

In order to rigorously document the economic and social impact of the financial services it provided to its rural customer base, KGFS agreed to open 50 bank branches in randomly chosen service areas in three districts of rural Tamil Nadu where they were planning to expand coverage (Ariyalur, Pudukkottai and Thanjavur). The unit of randomization was the bank branch service area, each of which covered approximately 10,000 people (2,000 households) living in 5-12 villages within a 4-5 km radius.

As part of the impact evaluation, KGFS adminstrators first worked with the research team to identify 100 service areas in these districts that were appropriate for expansion.[5] To maximize statistical power, service areas were then paired by the researchers according to geographic location and observable characteristics of the catchment population, and then treatment was randomly assigned within each pair.[6] Between 2009 and 2012, the bank proceeded to open new branches in these 50 randomly chosen locations, and refrained from doing so for at least two years in the corresponding control service areas. Figure 1 shows the location of each of the 50 pairs of service areas included in our study.

To evaluate the impact of bank branches, we sampled 46 households in each service area

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

[6] 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.

to survey prior to branch opening (baseline) and two years after opening (endline), for a total core analysis sample of 4,575 households. Figure 2 provides a graphic representation of the study sample.[7] Due to non-response among 415 households, our final analysis sample consists of 4,160 households, reflecting an average attrition rate in the sample of 9%, which is balanced across treatment and control service areas. Whenever possible, we augment the core sample with data from an additional 10,201 households for which we have limited information on income, poverty and employment.[8] Baseline data collection occurred alongside branch expansion, between 2010 and 2014 (in three different rounds), and the endline was administered between 2013 and 2016 (again, in three different rounds). Attrition between baseline and endline is minimal and not statistically different across treatment groups.[9]

Our baseline and the endline surveys collected detailed information on the socio-economic profile of the core sample, including: household income, consumption and expenditures; mental health indicators; outstanding and repaid loans, savings accounts and any insurance products; and household members' occupation and employment (wage labor or self-employment), and business outcomes (business sales and employment in the business). We compliment self-reported indicators of borrowing, saving, and insurance uptake with customer-product level administrative data from KGFS' Customer Management System (CMS).

[7]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.

[8]These data come from surveys conducted on a broader set households living in the same villages as our study sample.

[9]Respondent's migration and refusal to participate in the survey are among the main reasons for attrition.

Most of the survey was administered to the household head. However, two sections on health and wellbeing were specifically administered to a woman in the household who was chosen according to a distinct algorithm. At the end of these modules, we collected hair samples from the female respondent that were sent for laboratory analysis of hormone content in order to measure physiological stress responses. In particular, laboratory assays of hair samples measured stress biomarkers including cortisol, cortisone, and dehydroepiandrosterone (DHEA).[10] In total, 3,715 eligible women consented to be interviewed for the health section at endline. Of these, we collected hair samples from 3,241 after obtaining a second consent for hair collection (476 respondents refused to provide hair for laboratory analysis). Of those who consented, viable laboratory measurements for cortisol and cortisone were obtained for 2,968 and 2,966 of these women, respectively.[11] DHEA assay was not conducted until a mid-way through the endline data collection, which meant that DHEA levels were only measured for 2,099 of the women who provided hair samples.[12]

3 Empirical Approach and Results

We evaluate the impact of access to rural banks on household well-being by estimating the following regression:

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

[10]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.

[11]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.

[12]Of these 2,099 DHEA measurements, for 124 cases (5.9%) a non-detectable value was reported from the laboratory.

where y_{ik} is the outcome of interest for household i living in service area k in pair (stratum) p. 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.[13] 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 based on households' baseline monthly income levels. We divide our sample into income terciles, and estimate the following regression:

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

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 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). $HighIncome_i$ 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 summary statistics for our core household sample at baseline; overall, the treatment and control groups are balanced along the majority of observable characteristics, suggesting that the randomisation was successfully

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

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.

3.1 Impact on Income and Poverty

Our first set of results focuses on the impact of KGFS on income and poverty status. At baseline, our sample population was relatively poor, with roughly half of households below the poverty line, and had average monthly per capita income of 1,506 Rs (approximately ≈ $100 in 2011 PPP).[14]

Column 1 of Table 1 reports average treatment effects on income on the full village population. This sample includes both the core sample of 4,160 households and additional 10,200 observations from the village population census conducted in 937 villages in our service areas. We find a 14% significant increase in household income compared with the control group. Column 2 shows treatment impacts on poverty on the same sample. At endline, the treatment is associated with a significantly lower share of poor households (-9% of a control group mean of 33%). Column 3-5 of Table 1 show poverty results for the core sample. The probability of a household being poor at endline is 7.5% lower in treatment than control villages (Column 3). This result holds in significance and magnitude also when we restrict the analysis to households for which we have information on household income both at baseline and endline (2,565 households, Column 4). Column 5 adds to this analysis by showing the impact of rural banking on households' likelihood to transition out of poverty. The outcome variable in Column 5 is the probability that a household in the core sample that was poor

[14]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 A2 provides detailed variables definitions.

at baseline moved out of poverty at endline. Consistent with the results shown in column 1-4, 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 1 show that the expansion of KGFS succeeded in significantly reducing poverty rates in treated village, indicating substantial welfare gains to relatively poor households of banking services in rural areas. But how did access to formal financial services improve living conditions among even the poorest rural villagers? In the next section, heterogeneity analysis based on households' initial income levels helps us explaining the mechanisms behind our results.

3.2 Impact on Income, Wealth and Mental Health

Panel A of Table 2 presents average treatment effects on income, wealth and mental health for the core household sample; Panel B replicates the analysis of Panel A restricting the survey sample to those observations for which we have also baseline income information. Panel C shows heterogeneous treatment effects on these outcomes using baseline income levels, as estimated through Equation 2.

Average monthly income in the household sample, reported in Column 1, Panel A of Table 2 is 13% larger in the treatment than in the control group. This result confirms the significance and the magnitude of the treatment effect on household income for the census sample shown in Column 1 of Table 1.

We consider two additional outcomes that are likely to be impacted by improved formal financial access: household wealth and women's mental health. The analysis of the latter outcome is motivated by the fact that the main KGFS product is a JLG loan specifically targeting women.

We measure wealth through a standardized index of households' durables, including land, electrical appliances like fans, smartphones, and cookers, and vehicles like bicycles, motorcycles and rickshaws.[15] Column 2, Panel A of Table 2 shows positive and significant treatment effects on household wealth, with assets index being +0.03 standard deviation significantly higher in the treatment group.

Although increased borrowing is likely to have affected women's mental health, whether debt has a positive or a negative effect on borrowers' stress levels is still under debate (Sweet et al., 2013). Poverty alleviation associated with better financial systems (Levine, 2005; Beck et al., 2007) should reduce stress as the poor experience better living conditions. But managing high levels of debt may increase stress hence offset the psychological gains of reduced poverty. Moreover, the literature tackling this question has mostly relied on self-reported measures of psychological wellbeing, which are prone to subjectivity and recall bias. A number of studies have shown a positive association between poverty and mental-health issues using self-reported information (Mullainathan and Shafir, 2013; Schilbach et al., 2016), with few exceptions complementing subjective measures of stress with objective measures gathered from saliva biomarkers (Haushofer and Shapiro, 2016). Conversely, the literature on the relationship between debt and stress is thinner and less conclusive. Fernald et al. (2008) find positive effects on improved credit access on men, but no effects on women. This is surprising as women are disproportionately more likely to receive microfinance loans hence to experience the psychological consequences of increased debt.

We advance the knowledge on relationship between financial access and mental health by rigorously measuring women's stress levels following the expansion of KGFS through the collection of hair as a biomarker of stress. Stress biomarkers represent "objective" measures of mental health as they allow to measure levels of stress hormones like cortisol, dehydroepiandrosterone (DHEA), and cortisone in the human body. 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 se-

[15] 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.

cretion over the 3-month period prior to hair sampling versus a one-day as in the case of saliva (Stalder and Kirschbaum, 2012). This allows our study to be the first to estimate the impacts of formal financial access on individuals' chronic stress.[16]

Hair samples to detect and measure stress hormones were only collected at endline. From these samples, we obtain measures of cortisol and DHEA (pg/mg) for 2,091 and 2,952 women, respectively. We then combine levels of cortisol and DHEA at the subject level into a standardized index.[17]

Treatment effects on women's psychological well-being, measured through this stress biomarkers index, are shown in Column 3, Panel A of Table 2. 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 impacts on stress of formal debt.[18]

We next look for variation in treatment effects according to baseline income levels. Results in Panel C of Table 2 show that the main effects on income are concentrated among poorest and wealthiest households, although the difference is not statistically significant at conventional

[16]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).

[17]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' asset ownership: 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.

[18]We estimate equation 1 and 2 also for DHEA and cortisol, separately. 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.

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 2 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.

3.3 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 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.

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.

When KGFS began its operation in rural Tamil Nadu in 2009, the financial landscape mainly consisted of nationalised banks and informal lenders. 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).

The rural markets we study lacked, at the outset of KGFS expansion, the presence of a formal financial institution offering door-to-door, affordable banking products to rural households. Yet, households' engagement with the financial sector, particularly with the informal one, was quite high even in absence of microfinance. Panel C of Table A1 draws a picture of the financial lives of households at baseline, showing that about 70% of the households in our study sample had an outstanding loan with an informal lender before the expansion of KGFS.[19] A lower, but still non-negligible share of households (around 60%), also borrowed from the formal financial sector, and predominantly from state-run banks. All in all, more than half of households' total borrowing was informal.

These statistics highlight two main facts: first, KGFS expanded in areas where households were already familiar with financial services and products; second, our study sample was highly indebted, especially with informal lenders. The entrance of KGFS in the study villages may have pushed households to switch expensive informal credit with cheaper, formal loans.

To test this hypothesis, we look at KGFS products take-up rates from administrative data in Figure A1. Take-up rates are 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.[20] 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

[19] 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).

[20] 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.

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 administrative data on financial product take up. Results from estimating equation 1 on financial outcomes are shown in Table 3. Column 1, Panel A of Table 3 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.[21] 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 3 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.

[21] 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.

All in all, Panel A and B of Table 3 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 informal financial access in Panel C of Table 3. Formal financial inclusion and formal borrowing in particular have increased across the income spectrum. Column 5-6 of Panel B of Table 3 report heterogeneous treatment effects on informal borrowing. Better-off households drive the reduction in informal borrowing (Column 5 and 6).

3.3.1 Usage of Formal Loans

Taken together, results from Table 2 and Table 3 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 4 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 4 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 to a higher extent.

Results from Table 4 indicate that relatively better-off households used their formal loans for business growth, while poorer households did not use formal loans for income-generating activities. These findings are in line with the literature on the determinants of economic growth in presence of financial constraints (Banerjee and Newman, 1993; Aghion and Bolton, 1997; Evans and Jovanovic, 1989), and speak in favor of the existence of indirect effects triggered by increased formal financial access, whereby greater investment in productive activities generated positive impact in the local economic activity.

3.4 Testing spillover effects: Impact on Occupations and Employment

We estimate treatment effects on agriculture and non-agriculture labor to study how the expansion of KGFS affected households' occupations. We then study impacts on business outcomes (business sales and employment) and wages to assess economy-wide effects.
At the beginning of the study, 62% of study households had at least one member working in agriculture, with no statistically-significant difference across treatment and control villages (Panel D of Table A1). At the same time, less than one in five households (17%) 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, the low level of self-employment at baseline is suggestive of binding financial constraints in our study population.

We estimate treatment effects on occupations and business outcomes in Table 5. As with the previous analysis, Panel A shows average treatment effects for the full study sample (n=4,160), while Panel B restricts the analysis to the panel sample Column 1, Panel A consider differences at endline in the probability households report having at least one member working in the non-agricultural sectors. We do observe a significant increase in the likelihood that at least one member in treated households is employed in the non-agriculture sector, either as self-employed or a wage laborer. This result is mirrored into a lower reliance of treated households exclusively on the agricultural sector (-8.6% of control group mean of 0.35), as shown by Column 2 of Panel A of Table 5. Column 3-5 of Panel A and Panel B consider business outcomes. We find a significant expansion in self-employment both in terms of business sales (+21%), business wealth (+25%)[22], and employment. Households in treated villages are also 33% more likely to employ individuals outside the household in the business activity (+0.01 of control mean of 0.03).

Panel C of Table 5 presents heterogeneous treatments effects on occupations and employment-related outcomes. Treatment effects appear concentrated among better-off households, who are significantly more likely to have a member working 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 5, together with previous findings, indicate a clear, positive link between access to formal loans, poverty reduction and larger investments undertaken by wealthier villagers. These findings provide further support to our main hypothesis that formal financial access has increased investment in and returns from self-employment by relaxing financial constraints for better-off households, while also benefiting less entrepreneurial ones through increased labor opportunities.

To additionally test this mechanism, we estimate treatment effects on wages, both from our core sample and the village sample. Results are shown in Panel A of Table 6. While estimates

[22]Business wealth is measured as the total monetary value of inventory and equipment in the business activity

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.[23]

4 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 MFI that offering 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 6% more likely to report one member working outside agriculture, at

[23] 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.

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.

References

Aghion, P. and P. Bolton (1997). A theory of trickle-down growth and development. *The Review of Economic Studies 64*(2), 151–172.

Angelucci, M., D. Karlan, and J. Zinman (2015). Microcredit impacts: Evidence from a randomized microcredit program placement experiment by compartamos banco. *American Economic Journal: Applied Economics 7*(1), 151–82.

Banerjee, A., E. Breza, E. Duflo, and C. Kinnan (2019). Can microfinance unlock a poverty trap for some entrepreneurs? Technical report, National Bureau of Economic Research.

Banerjee, A., E. Duflo, R. Glennerster, and C. Kinnan (2015). The miracle of microfinance? evidence from a randomized evaluation. *American Economic Journal: Applied Economics 7*(1), 22–53.

Banerjee, A. V. and A. F. Newman (1993). Occupational choice and the process of development. *Journal of Political Economy 101*(2), 274–298.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2007). Finance, inequality and the poor. *Journal of economic growth 12*(1), 27–49.

Belloni, A., V. Chernozhukov, and C. Hansen (2014, May). High-Dimensional Methods and Inference on Structural and Treatment Effects. *Journal of Economic Perspectives 28*(2), 29–50.

Breza, E. and C. Kinnan (2018). Measuring the equilibrium impacts of credit: Evidence from the indian microfinance crisis. Technical report, National Bureau of Economic Research.

Bruhn, M. and I. Love (2014). The real impact of improved access to finance: Evidence from mexico. *The Journal of Finance 69*(3), 1347–1376.

Burgess, R. and R. Pande (2005). Do rural banks matter? evidence from the indian social banking experiment. *American Economic Review 95*(3), 780–795.

Célerier, C. and A. Matray (2019). Bank-branch supply, financial inclusion, and wealth accumulation. *The Review of Financial Studies 32*(12), 4767–4809.

Crépon, B., F. Devoto, E. Duflo, and W. Parienté (2015). Estimating the impact of microcredit on those who take it up: Evidence from a randomized experiment in morocco. *American Economic Journal: Applied Economics 7*(1), 123–50.

Evans, D. S. and B. Jovanovic (1989). An estimated model of entrepreneurial choice under liquidity constraints. *Journal of political economy 97*(4), 808–827.

Fernald, L. C., R. Hamad, D. Karlan, E. J. Ozer, and J. Zinman (2008). Small individual loans and mental health: a randomized controlled trial among south african adults. *BMC public health 8*(1), 409.

Gao, W., C. Kirschbaum, J. Grass, and T. Stalder (2016). Lc–ms based analysis of endogenous steroid hormones in human hair. *The Journal of steroid biochemistry and molecular biology 162*, 92–99.

Ghatak, M., M. Morelli, and T. Sjöström (2007). Entrepreneurial talent, occupational choice, and trickle up policies. *Journal of Economic Theory 137*(1), 27–48.

Haushofer, J. and J. Shapiro (2016). The short-term impact of unconditional cash transfers to the poor: experimental evidence from kenya. *The Quarterly Journal of Economics 131*(4), 1973–2042.

Kaboski, J. P. and R. M. Townsend (2012). The impact of credit on village economies. *American Economic Journal: Applied Economics 4*(2), 98–133.

King, R. G. and R. Levine (1993). Finance and growth: Schumpeter might be right. *The quarterly journal of economics 108*(3), 717–737.

Kling, J. R., J. B. Liebman, and L. F. Katz (2007). Experimental analysis of neighborhood effects. *Econometrica 75*(1), 83–119.

La Porta, R., F. Lopez-de Silanes, and A. Shleifer (2002). Government ownership of banks. *The Journal of Finance 57*(1), 265–301.

Levine, R. (2005). Finance and growth: theory and evidence. *Handbook of economic growth 1*, 865–934.

Lloyd-Ellis, H. and D. Bernhardt (2000). Enterprise, inequality and economic development. *The Review of Economic Studies 67*(1), 147–168.

Meager, R. (2019). Understanding the average impact of microcredit expansions: A bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics 11*(1), 57–91.

Mullainathan, S. and E. Shafir (2013). *Scarcity: Why having too little means so much.* Macmillan.

Rajan, R. and L. Zingales (1998). Financial development and growth. *American Economic Review 88*(3), 559–586.

Schilbach, F., H. Schofield, and S. Mullainathan (2016). The psychological lives of the poor. *American Economic Review 106*(5), 435–40.

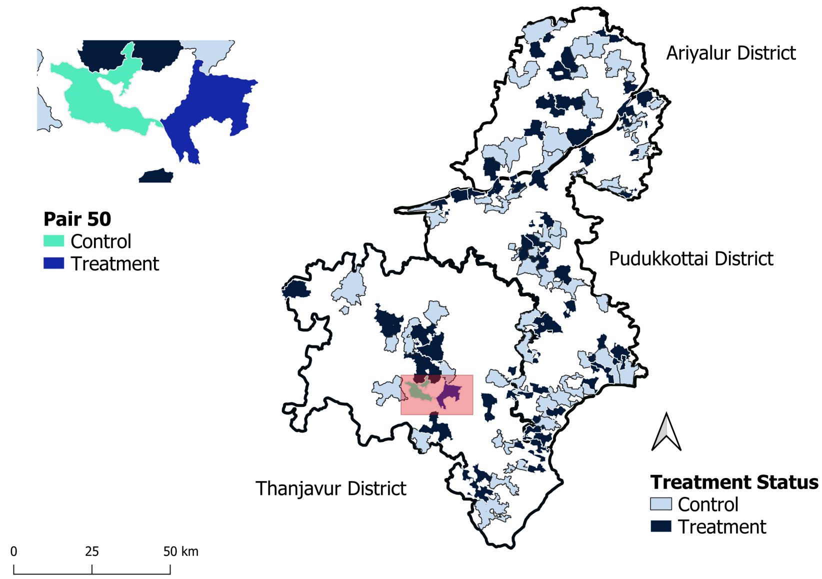
Stalder, T. and C. Kirschbaum (2012). Analysis of cortisol in hair–state of the art and future directions. *Brain, behavior, and immunity 26*(7), 1019–1029.

Sweet, E., A. Nandi, E. K. Adam, and T. W. McDade (2013). The high price of debt: Household financial debt and its impact on mental and physical health. *Social Science & Medicine 91*, 94–100.

Walther, A., C. Tsao, R. Pande, C. Kirschbaum, E. Field, and L. Berkman (2019). Do dehydroepiandrosterone, progesterone, and testosterone influence women's depression and anxiety levels? evidence from hair-based hormonal measures of 2105 rural indian women. *Psychoneuroendocrinology 109*, 104382.

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

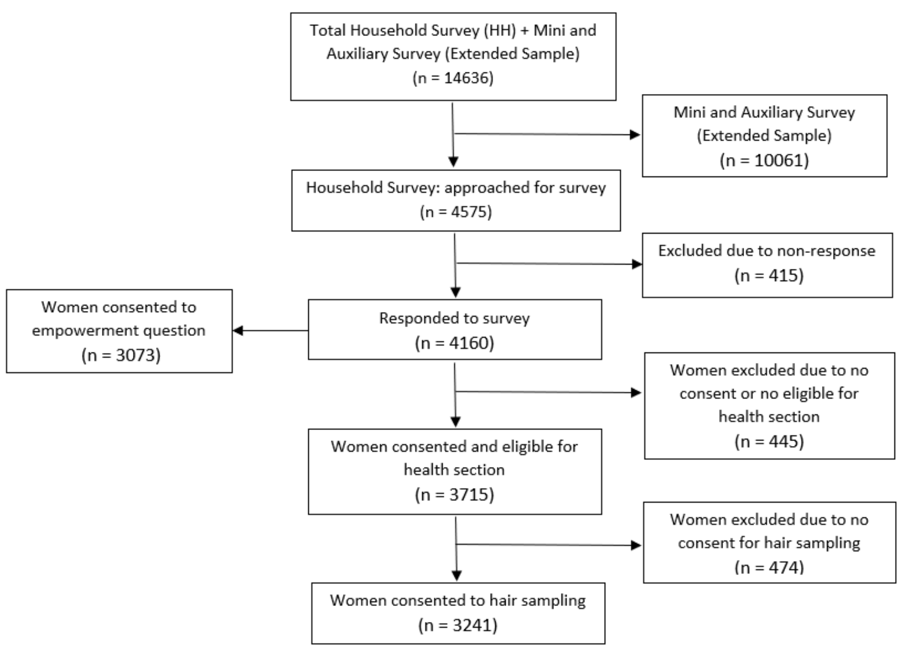


Table 1: Treatment Effects on Poverty Rates

	HH income (Census sample)	Poor (Census sample)	Poor (HH sample)	Poor (HH / BL income sample)	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)**
Control Dep Var Mean	8.21	0.33	0.40	0.39	0.29
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 consumption for 3,826 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 2: Treatment Effects on Income, Wealth and Mental Health

	HH Income (log)	HH Income (log) (Stress Sample)	Asset Index	Stress Index
Panel A: Intention-To-Treat Effects				
	(1)	(2)	(3)	(4)
Treated	0.13	0.14	0.03	-0.07
	(0.05)**	(0.06)**	(0.01)**	(0.02)***
Control Dep Var Mean	8.16	8.32	0.00	0.00
N	4158	2952	4159	2953
Panel B: Intention-To-Treat Effects (Income Panel Sample)				
	(1)	(2)	(3)	(4)
Treated	0.23	0.20	0.03	-0.07
	(0.07)***	(0.08)***	(0.01)***	(0.02)***
Control Dep Var Mean	8.15	8.32	0.00	0.08
N	2565	1846	2566	1847
Panel C: Heterogenous Treatment Effects by BL Income Terciles				
	(1)	(2)	(3)	(4)
γ_1: Low Income at BL X Treated	0.27	0.10	0.05	-0.12
	(0.16)*	(0.16)	(0.02)**	(0.04)***
γ_2: Middle Income at BL X Treated	0.16	0.15	0.02	0.00
	(0.13)	(0.13)	(0.02)	(0.04)
γ_3: High Income at BL X Treated	0.28	0.43	0.04	-0.09
	(0.16)*	(0.18)**	(0.03)	(0.05)*
Control Dep Var Mean Low Income	7.62	8.02	-0.11	0.13
Control Dep Var Mean Middle Income	8.24	8.38	-0.01	0.05
Control Dep Var Mean High Income	8.58	8.53	0.13	0.06
N	2565	1846	2566	1847
$\gamma\_1 = \gamma\_2$ (P-value)	0.61	0.82	0.45	0.02
$\gamma\_1 = \gamma\_3$ (P-value)	0.97	0.24	0.82	0.56
$\gamma\_2 = \gamma\_3$ (P-value)	0.57	0.26	0.65	0.14

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 2 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 2,750 households from the core sample. Asset Index (column 3) 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 3: 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)**
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 (Income Panel Sample)						
	(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)**
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 Effects by BL Income Terciles						
	(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)
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 consumption for 2,750 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 4: Treatment Effects on Usage of Formal Loans

	Farming/Business Investment	Health	Migration Costs	Education	Rent	Repay Old Debt	House/Land Repairs or Upgrade	Jewlery 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	359.57	-58.79	-59.71	-11.50	461.61	819.19	251.93	-210.34	197.32
	(1291.67)***	(175.79)**	(152.82)	(270.83)	(3.47)***	(117.22)***	(876.42)	(75.46)***	(434.73)	(180.68)
Control Dep Var Mean	12862.09	1585.28	1141.14	3368.47	12.94	1081.83	16713.80	477.01	4497.61	3382.76
N	4146	4146	4146	4146	4146	4146	4146	4146	4146	4146
Panel B: Intention-To-Treat Effects (Income Panel Sample)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	4679.01	182.25	11.73	-131.33	-2.41	366.23	397.40	111.36	-194.49	98.75
	(1722.38)***	(218.76)	(212.58)	(278.33)	(2.32)	(132.97)***	(1194.57)	(64.36)*	(572.77)	(241.31)
Control Dep Var Mean	13995.86	1509.96	1163.02	3097.94	3.52	777.28	19186.06	499.02	4892.48	3594.93
N	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560
Panel C: Heterogeneous Effects by BL Income Terciles										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
γ_1: Low Income at BL X Treated	3272.98	-582.60	-16.42	1095.85	-9.89	433.25	2026.72	173.13	708.18	131.38
	(2290.83)	(470.83)	(313.20)	(669.46)	(8.88)	(313.63)	(2381.42)	(170.08)	(1040.36)	(528.79)
γ_2: Middle Income at BL X Treated	6682.02	27.26	207.46	-99.20	1.78	39.29	-1290.01	-38.57	-700.19	151.78
	(2704.92)**	(528.83)	(537.91)	(629.85)	(2.90)	(312.44)	(2661.83)	(184.10)	(1022.75)	(444.42)
γ_3: High Income at BL X Treated	3967.84	1173.52	-78.46	-1265.89	0.68	657.87	750.59	213.37	-537.87	110.22
	(3836.45)	(609.89)*	(548.46)	(785.39)	(1.69)	(316.90)**	(3103.98)	(205.96)	(1051.28)	(550.89)
Control Dep Var Mean Low Income	10663.49	1707.58	504.45	1861.24	10.93	694.29	15132.85	398.41	4028.55	2970.14
Control Dep Var Mean Middle Income	10619.07	1505.92	1128.30	2891.79	0.00	761.91	16664.98	607.09	5438.67	3496.01
Control Dep Var Mean High Income	21168.89	1314.93	1867.32	4579.42	0.00	878.42	26122.33	478.79	5149.22	4337.51
N	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560
$\gamma\_1 = \gamma\_2$ (P-value)	0.33	0.43	0.73	0.21	0.29	0.39	0.39	0.43	0.36	0.98
$\gamma\_1 = \gamma\_3$ (P-value)	0.88	0.03	0.93	0.04	0.28	0.67	0.76	0.90	0.39	0.98
$\gamma\_2 = \gamma\_3$ (P-value)	0.57	0.23	0.74	0.32	0.42	0.22	0.67	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 consumption for 2,750 households from the core sample. We include in the regression the best controls selected through lasso (OLS regression).

Table 5: Treatment Effects on Occupations and Employment

	Any Non-Agri	Agri Only	Log Sales Self-Emp (30 days)	Log Business Wealth	Employs non-HH members
Panel A: Intention-To-Treat Effects					
	(1)	(2)	(3)	(4)	(5)
Treated	0.03	-0.03	0.21	0.25	0.01
	$(0.01)^{**}$	$(0.01)^{**}$	$(0.07)^{***}$	$(0.08)^{***}$	$(0.00)^{**}$
Control Dep Var Mean	0.51	0.35	1.24	1.34	0.03
N	4160	4160	4143	4149	4156
Panel B: Intention-To-Treat Effects (Income Panel Sample)					
	(1)	(2)	(3)	(4)	(5)
Treated	0.04	-0.04	0.30	0.33	0.00
	$(0.02)^{**}$	$(0.02)^{**}$	$(0.08)^{***}$	$(0.10)^{***}$	(0.00)
Control Dep Var Mean	0.52	0.36	1.16	1.28	0.03
N	2567	2567	2555	2556	2565
Panel C: Heterogeneous Effects by BL Income Terciles					
	(1)	(2)	(3)	(4)	(5)
γ_1: Low Income at BL X Treated	0.06	-0.05	0.15	0.18	-0.00
	$(0.03)^{*}$	(0.03)	(0.16)	(0.18)	(0.01)
γ_2: Middle Income at BL X Treated	0.04	-0.03	0.44	0.40	-0.00
	(0.03)	(0.03)	$(0.15)^{***}$	$(0.18)^{**}$	(0.01)
γ_3: High Income at BL X Treated	0.02	-0.05	0.31	0.40	0.02
	(0.03)	$(0.03)^{*}$	(0.23)	(0.27)	$(0.01)^{*}$
Control Dep Var Mean Low Income	0.37	0.47	0.61	0.68	0.02
Control Dep Var Mean Middle Income	0.55	0.33	1.00	1.11	0.02
Control Dep Var Mean High Income	0.63	0.28	1.91	2.09	0.05
N	2567	2567	2555	2556	2565
$\gamma\_1 = \gamma\_2$ (P-value)	0.61	0.76	0.21	0.44	0.81
$\gamma\_1 = \gamma\_3$ (P-value)	0.36	0.98	0.58	0.51	0.16
$\gamma\_2 = \gamma\_3$ (P-value)	0.66	0.75	0.68	1.00	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 consumption for 2,750 households from the core sample. All outcomes are measured using endline data. Column (1), the definition of any non-agricultural 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 indicates household works in only any agricultural wage labor and not work in any non agricultural wage labor. 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).

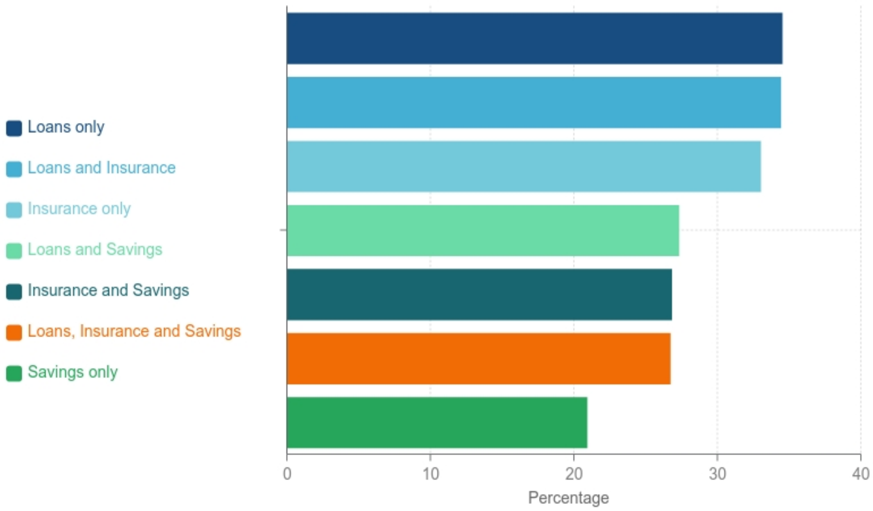
Table 6: Treatment Effects on Wages

	Log Wage Labor Income (daily), HH survey	Log Wage Labor Income (weekly), HH survey	Log Total Weekly Wages, Mini Sample
Panel A: Intention-To-Treat Effects			
	(1)	(2)	(3)
Treated	0.04	0.06	0.06
	(0.06)	(0.08)	(0.03)**
Control Dep Var Mean	3.52	4.35	7.14
N	4160	4160	2293
Panel B: Intention-To-Treat Effects (Income Panel Sample)			
	(1)	(2)	
Treated	0.08	0.09	
	(0.09)	(0.11)	
Control Dep Var Mean	3.52	4.35	
N	2567	2567	
Panel C: Heterogeneous Effects by BL Income Terciles			
	(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)	
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).

5 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	0.31	0.04**	4053
	[0.46]	(0.04)	
Scheduled Caste and Tribe	0.25	-0.00	4053
	[0.44]	(0.03)	
Household Own Land	0.55	-0.00	4064
	[0.50]	(0.04)	
Panel B: Income, Consumption and Poverty			
Per capita HH Consumption (30-day), topcoded	767.87	-4.91	4063
	[550.50]	(36.27)	
Per capita HH Income (30-day), topcoded	1505.81	126.38	2727
	[2171.98]	(164.94)	
Below Poverty Line (using Consumption), topcoded	0.77	0.02**	4062
	[0.42]	(0.02)	
Below Poverty Line (using Income), topcoded	0.53	-0.00	2726
	[0.50]	(0.03)	
Panel C: Borrowing, Saving, and Insurance Outcomes			
Household has Outstanding Formal Loan(s)	0.61	0.00	4052
	[0.49]	(0.02)	
Household has Outstanding Informal Loan(s)	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)	

	Control Mean [SD]	**Coefficient** difference (SE)	**N**
	[1]	[2]	[3]
Informal Share of Tot. Outstnd Ratio	0.48	-0.01	3805
	[0.43]	(0.02)	
Panel D: Occupations, Employment, and Wages			
At Least 1 HH Mbr 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)	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: 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 A3: 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/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. Variables are Rupees amount and top coded at 3 standard deviations from the mean.

Note: These variables are used in Table 3.

Table A4: 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 A5: 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 A5: 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.