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Branchless Banking: Evaluating the Doorstep Delivery of Financial Services in Rural India

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Abstract

This paper evaluates the effect on household savings of India's recent financial inclusion drive, a drive that generated an unprecedented increase in access to financial institutions by using mobile technologies to deliver services practically at the doorstep of rural households. Using household data from just before and after the initiation of the policy, matched with village-level data on financial institutions, I identify the effects of access to financial institutions utilizing longitudinal variation in conjunction with geographic eligibility criterion that provided services to villages based on the size distribution of villages in the service area assigned to the bank.

JEL Codes: G21, O12, O16
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1. Introduction

Governments of most developing economies have made universal access to financial services a priority, complementing efforts by international agencies such as the World Bank to ensure universal financial access by 2020. To achieve these targets, many governments, including those of Brazil, Colombia, Peru, Mexico, Argentina, Venezuela and India are using local agents who enable branchless banking through the use of new mobile technologies. For most households, access to financial services is increasingly through such agents. In India, for example, local agents, known as business correspondents (BCs), accounted for 51% of total banking outlets in March 2010 (representing 34,316 of a total of 67,694 outlets). Just 5 years later, by March 2015, the number of banking outlets had increased dramatically to 553,713. Of this, as many as 91% represented branchless outlets, primarily business correspondents (Reserve Bank of India 2015).[1]

Governments' support for branchless banking through local agents is premised on the belief that this delivery model may be the most effective method of ensuring financial inclusion and, correspondingly, of enabling all households to join the formal economy. One reason is its significantly lower costs relative to a model of financial inclusion based on the expansion of "brick-and-mortar" bank branches. Additionally, branchless banking has generally been accompanied with new regulation that enables basic savings accounts with very low fees, hence reducing direct costs to households. More significant than the reduction in direct costs, however, is that in the opportunity costs borne by households. Armed with mobile devices, such as POS (point of service) instruments, local agents enable households to make both deposits and withdrawals from their homes. The delivery of financial services "at the doorstep" essentially eliminates opportunity costs associated with financial transactions through bank branches.

The use of agents additionally allows the financial system to address behavioral factors such as inattention or temptation that are known to affect savings (Mullainathan and Shafir 2013). Because BCs earn their income through a commission fee on each transaction, they have an incentive to "nudge" households to save on a regular basis. The BC model is also well-suited to ensure the "timeliness" of reminders, supporting academic research that documents the importance of reminders at the most opportune time (Karlan, McConnell, Mullainathan and Zinman 2010). Their local residence, mobility and unrestricted hours makes it possible for BCs to even transact with individuals as they return home from a day of work in the labor market with

[1] Other branchless banking options, ATMs and Mobile Vans, account for only 0.05% of branchless banking outlets.

wages in hand. A final advantage of the BC model is the fact that agents are normally drawn from the local community and have higher-than-average education levels. Being well-known amongst the community, they can work within village networks to encourage savings.

However, a model based on local agents also has its disadvantages. A long tradition in economics, dating back to Marshall (1920) and Young (1928), has noted that while the local provision of non-tradeable services, including financial services, can enhance productivity and hence growth, the viability of local providers will be limited by the size of the market, if their operations are characterized by decreasing average costs. In turn, the dependence on local demand can generate sustained poverty and poverty traps in poor economies (Rodrigues-Clare 1996; Okuno-Fujiwara 1988; Ciccone and Matsuyama 1996). Additionally, local agents may exacerbate geographic inequalities: If decreasing average costs reflect transportation costs that increase with distance, then the financial viability of local providers will be greater in regions with a higher degree of geographical concentration or density (Krugman 1990, 1996; Ciccone and Hall 1993). This suggests that the use of local agents may enhance the returns to agglomeration or geographic concentration, increasing regional inequalities.

Cognizant of concerns regarding the financial viability of local agents, governments have accompanied branchless banking policies with several measures intended to ensure agents' profitability. One such measure relates to agents' commissions. Business correspondents generally earn a commission per transaction, with this commission being paid by the bank, rather than the customer. Additionally, and perhaps more importantly, governments are increasingly providing welfare payments and other transfers to households through saving bank accounts, allowing local agents to earn a commission on each such transaction. This ensures income to business correspondents, even in regions where the demand for financial transactions might otherwise be low. Finally, governments frequently demarcate the geographic area to be covered by each agent. For example, India's experiment in branchless banking is based on a geographic mapping exercise that (roughly) assigns each village government or Gram Panchayat (GP) to a single business correspondent. While households are free to seek out BC's assigned to other GPs, the hope is that this exercise in geographical mapping will ensure a viable market size for each agent and also facilitate the link with poverty programs, given that these programs are generally implemented by the Gram Panchayat.

The tie-up with welfare programs as well as the fact that BCs earn a commission on each transaction may create incentives for BCs to serve poor households. Welfare payments are automatically deposited in beneficiary bank accounts, with BCs earning a commission each time the household withdraws earnings. Because payments under MNREGA, as well as payments for wage work done in the regular unskilled labor market, are generally made every two weeks, the number of transactions by labor households exceed those of non-labor households, whose primary source of earnings is profits from their farms. Farm incomes generally accrue only at the time of harvests, so that the income profile of non-labor households demonstrates very low frequency. Under such conditions, the viability of BC's may primarily depend on the number of poor households in a village, reversing predictions of sustained poverty as a consequence of increasing returns to scale in the provision of financial services.

There is little evidence on whether these experiments in branchless banking have succeeded in increasing household saving, or on the factors that may influence the effectiveness of BCs. Anecdotal evidence is mixed. While the program's web page (http://www.pmjdy.gov.in) states that 200 million bank accounts had been opened over the course of one year, several media reports note that a large number of accounts are dormant, and that the program has not increased financial savings.[2]

In this paper, I use household data from the state of Karnataka, in south India, to evaluate the impact on household savings of coverage under India's branchless banking program, the largest such program to have ever been implemented. My analysis is based on two rounds of household surveys implemented just prior to and a few years after the introduction of the policy, with the second round conducted while the program was still being phased in. The data provide village identifiers, as well as identifiers for the Gram Panchayat (GP), the lowest level of elected government in India, in which the village is located.[3] Using these identifiers, I match the household data with a rich "financial inclusion" data base that provides information on the availability of BCs and branches, at the level of the village, both prior to and after the introduction of the program. Additionally matching the data set to census data, I am able to construct the entire geography of the GP in which survey villages are located. Data on

[2] http://www.ndtv.com/india-news/truth-vs-hype-jan-dhans-half-empty-promise-763720; http://scroll.in/article/769613/jan-dhan-yojana-on-paper-a-radical-scheme-on-the-ground-a-catalyst-for-confusion-and-coercion

[3] In survey districts, each GP includes an average of 7 villages.

household's actual use of a BC or bank branch is, however, unavailable. This research therefore recovers estimates of the effect of coverage or access, as defined by the program, rather than that of usage of financial outlets. As is generally the case with program evaluations, the results of this paper also represent an evaluation of a specific program; the results may not hold under changes in the rules that dictate coverage.

The richness of the data set makes it possible to exploit the determinants of the phased implementation of the program. While the ultimate objective of the program was to ensure coverage of each GP by a BC, a 2009 policy dictated that BCs would first be provided to GPs with a village of a population of 2000 or more that were not served by a bank branch. At the time of our end-line survey (February 2013), the allocation of BCs to GPs was still far from complete, and followed this rule.

The strength of the identification strategy comes from the uniqueness of this rule. As in many other policies, the rule defined specific cut-offs that determined eligibility. However, in this instance, eligibility cut-offs were based on the geographies of GPs: BCs were to be provided in all previously "unbanked" GPs that included a village of population size 2000 or more. The program is the only one in India to use a geographic targeting model whereby the population of the largest village in the GP determines the access of all other villages to financial services. This means that the access to financial outlets of two villages, with the same population, could differ, depending on the size of other villages in the GP. I provide empirical support for identification based on this geographic cut-off through a number of falsification tests. A first set of regressions evaluates whether other cut-off levels also predict the assignment of BCs. A second set utilizes regression samples that are restricted to narrow intervals around the stipulated cut-off, and tests the effect of the geographic cut-off on coverage by a BC and on household savings.

Identification is further strengthened by the availability of two rounds of data, one prior to the commencement of the policy and the second during its phase-in period. This enables a standard difference-in-difference estimator. However, because the program was phased in over identified eligible units, compliance was imperfect, suggesting that the difference-in-difference model would recover only ITT estimates. As in a fuzzy regression discontinuity design, combining the difference in difference framework with an instrumental variable approach (IV-DiD), utilizing the eligibility rules as instruments, recovers causal effects of the effect of coverage by BCs on household outcomes.

The strongest results of this paper relate to the effect of BCs on (total) household savings, financial savings and savings in other assets. However, I also provide suggestive evidence on pathways of influence. If, in addition to any direct effect on the return to savings accounts, BCs also enable improvements in wage earnings, then wage earnings and hours of wage work will be greater in GPs covered by a BC. This increase in income, unless fully consumed, will further augment savings, though not necessarily in bank accounts. I test for such effects by classifying households by land-ownership as "labor" or "non-labor" households. I then run regressions for total savings, savings by asset type, household expenditure, income and hours of work on the indicator variable for coverage by a BC, allowing the coefficient on BC to vary by land ownership and treating the interacted variable as endogenous. I also test some of the predictions of models of local banking in the presence of fixed costs. This is particularly important in the context of developing economies, given predictions that the local delivery of services may contribute to sustained poverty and exacerbate inequalities based on the economic geography of local markets.

I find that BCs significantly increase total household savings and savings in bank accounts, suggesting the potential to extend financial inclusion through the use of a technology-enabled model based on the local delivery of financial services. Dividing the sample into labor and non-labor households suggests important differences. As a consequence of BCs, the total savings of labor households increase *more* than that of non-labor households. This is primarily because BCs enable increases in the wage earnings of male and female members of labor households. The effect on wage earnings suggests that the large impact of BCs on labor households may reflect improvements in wage rates and the functioning of wage labor markets as a consequence of the tie-up between the financial inclusion program and the welfare program, MNREGA. The larger increase in savings of labor households is not matched by a commensurate increase in savings in bank accounts. Instead, I find some evidence that labor households tend to hold greater grain inventories in villages covered by a BC.

I also find that BCs have a larger effect on household savings in GPs with greater population concentration, and that their effect is greater for households who reside in the largest village in the GP. However, for any given village, the effect of coverage by a BC also increases with village population. This pattern of effects corresponds to those from regressions in which the dependent variable is household expenditure and non-wage earnings. Regressions on wage

earnings, particularly female wage earnings, generate an effect of BCs that increase with the number of poor households in a village, and also favor smaller villages. These results suggest that the tie-up with MNREGA, in addition to increasing the effect of the program on the savings of labor households, may also offset an increase in inequality that may otherwise accompany the introduction of financial services. I emphasize, however, that these conclusions are tentative. Though the regression findings are supportive of these conclusions, they may also be consistent with other alternative explanations.

The results of this paper contribute to a large body of research on household savings, particularly the impact of improved access to financial outlets. While the global experiment with branchless banking is relatively new, earlier research (Kochar 2011; Burgess and Pande 2005) has examined the effect of policies that expanded access to traditional banking outlets, specifically bank branches. This research, however, has generally been conducted at a high level of aggregation (the state or the district), primarily because of the lack of household-level or village-level information on access to financial institutions. The availability of village (and GP) identifiers in my data set not only enable a more disaggregated analysis, but also allows me to accurately exploit policy rules, which are based on the specific geographies of GPs. Additionally, the availability of household data allows me to examine effects on savings, income and expenditure, in contrast to the focus on household expenditure in other studies that rely on national household surveys that frequently provide information on household expenditure, but not on savings.

While there is scant research on the impact of a national program of branchless banking, a number of recent studies provide evidence on individual features or components of such programs. For example, research by Prina (2013) and Dupas, Green, Keats and Robinson (2012) examines the effect of costs on opening and maintaining savings accounts. Several studies also support the hypothesis that addressing behavioral constraints can impact savings. Specifically, research demonstrates that "nudging" households to save through constant reminders increases savings (Karlan et al 2010; Kast et al 2012). Similarly, contracts that commit households to saving goals have also proven to be effective (Ashraf et al 2006, Dupas and Robinson 2013), as has peer pressure through social networks (Breza and Chandrasekhar 2014). Combining some of these features, Breza and Chandrasekhar (2014) implement a field experiment in the Indian state of Karnataka, with one treatment arm designed to mimic the BC model. They find that this

treatment generates large effects on savings, though households generally fail to meet stated savings goals for formal accounts.

Breza and Chandrasekhar's (2014) research, and much of the other recent evidence on behavioral determinants and on access and administrative costs comes from randomized controlled trials (RCTs). There is far less evidence on whether these same mechanisms succeed when implemented on scale, in a non-experimental setting. To the best of my knowledge, this research represents one of the first studies of the effect on savings of a national program on branchless banking. As previously noted, India's program represents the largest such program ever undertaken.[4] The program's significant departure from historic financial inclusion policies, both in India and elsewhere, in terms of outreach, its unprecedented reduction in access costs, its tie-up with income generating policies, and its community based approach separates this policy from others. Correspondingly, the analysis of this paper provides insights on household's willingness to hold financial assets, relative to other income-generating assets, when technology makes possible a reduction in transaction costs to very low levels. [5] It also provides suggestive evidence of the effect of a tie-up between the provision of financial services and welfare programs.

The remainder of this paper is structured as follows. Section 2 describes India's financial inclusion and relevant welfare policies. Survey data and summary statistics are in Section 3. The theoretical framework underlying the empirical analysis of this paper is briefly described in Section 4, while the empirical framework is detailed in section 5. Sections 6 presents results while the last section concludes.

2. Financial Inclusion and Welfare Policies in India

2.1 Early financial inclusion policies

[4] The program has been continued under the current Indian government, under the name Jan Dhan Yojana. Data from the Ministry of Finance reveal that, as of January 2016, 200 million bank accounts have been opened under the scheme (http://www.pmjdy.gov.in).

[5] A growing body of research evaluates technologically-driven innovations in other fields: Jack and Suri (2014) examine the effect of Kenya's mobile money system on consumption smoothing; Muralidharan, Niehaus and Sukhtankar (2014) examine the effect of smartcards on India's welfare program; and Jensen (2004) and Aker (2010) examine the impact of mobile phones on price dispersion in India and Niger respectively.

India has a long history of policies intended to provide the poor access to formal financial markets. In the early 60s through the 1980s, financial inclusion policies took the form of the nationalization of commercial banks, directed or targeted lending to "priority sectors" such as agriculture and to "weaker sections" of society including the landless and small farmers, and the development of an extensive network of bank branches intended to ensure a uniform population to bank branch ratio (of 17,000) in each district of the country. This directed policy was overseen by a hierarchical institutional framework that stretched down to a district, with a "Lead Bank" appointed in each district to ensure compliance.

This first credit-led experiment in financial inclusion was discontinued in the early 1990s, due to high default rates on institutional loans and their adverse effect on the financial viability of formal rural financial institutions. Though the policy expanding the branch network in rural areas was suspended, branches were not closed and access to formal institutions remained relatively high. Despite this, India lagged behind other countries in standard measures of financial inclusion. Data from the World Bank's 2011 Findex Database reveal that only 35% of Indians (over the age of 15) have an account at a formal financial institution, while only 12% of adults reported savings in formal accounts in the past year.[6] Available data also reveal a sharp divide between the rich and the poor in the use of formal financial institutions. Data from a 2006-07 revealed that only 17.7% of individuals in the lowest income quartile, but 86% in the highest quartile, had a bank account.[7]

2.2 New policies

Reflecting the world-wide emphasis on financial inclusion, the Government of India announced several new policies, starting in 2005, to lower the costs of transacting with formal financial institutions. In November 2005, the Reserve Bank of India asked all banks to provide a basic "no frills" account that entailed a low or zero balance and charges. This move was accompanied by a relaxation and simplification of KYC (Know Your Customer) norms to facilitate the easy opening of bank accounts. A far-reaching policy was a January 2006 decision that permitted banks to use the services of non-government organizations, micro-finance

[6] In contrast, China and the US reported formal savings by 32% and 50% of their respective adult populations.
[7] Conducted by Invest India Market Solutions, cited in the report of the Rajan Committee on Financial Sector Reforms (Government of India 2009). This same study also reveals that the gap in financial access is primarily a rich-poor gap, not a rural-urban gap. Almost all individuals with incomes in excess of Rs. 200,000, utilize the services of formal financial institutions, irrespective of geographic location.

institutions and other organizations as business facilitators (BFs) or business correspondents (BCs). BFs primarily facilitated bank operations through doing preliminary paper work, processing of loan applications, creating awareness of new products, etc. BCs were additionally empowered to make disbursals, collect principal and interest payments, and make transactions from savings accounts. They could also handle insurance payments, pension payments, remittances and handle a variety of other financial services. BCs are specifically prohibited from charging fees to customers. Instead, they earn their income on commission fees, per transaction, born by banks. Later initiatives (2014) relaxed guidelines on who could be hired as a BC and norms regarding their distance from the bank branches they were attached to.

The real drive to ensure financial inclusion of all rural households began, however, in November 2009, when the Reserve Bank issued a directive requiring each Lead Bank to draw up a roadmap by March 2010 to provide banking services through a banking outlet – either a branch or a BC – in every village having a population of over 2000. The intent of this policy was to ensure that every village had access to at least one financial outlet. No restrictions were placed on households' choice of outlet, and they were not required to transact only with the BC or Branch assigned to their village. This mapping exercise was, indeed, undertaken by lead banks by March 2010. Lists of "unbanked villages" with a population of 2000 or more, not yet covered by bank branches or BCs, were drawn up for each district. The initial policy required the expansion of bank services to targeted villages be completed by March 2011, followed by the initiation of a second phase targeting villages of size 1650 or more. However, the date for the first phase, involving coverage of villages of size 2000 or more, was subsequently pushed back to March 2012 (RBI circular dated September 2010).

The second phase was never officially implemented because the initial policy was modified in October 2011 to promote a different approach for ensuring universal coverage. This new approach recognized the relatively small size of India's villages, and hence the difficulties of a village-based approach to financial inclusion. The Ministry of Finance noted that there were approximately 73,000 villages in the country with a population of 2000 and above, who would receive banking services under the new directive. This represented only 12% of India's 600,000 villages. To ensure wider coverage, the 2011 modification stated that appointed BCs should provide financial services not just to the village in which they were located, but also to a set of identified adjoining villages, so as to ensure coverage of all villages in the country.

For this purpose, the Reserve Bank defined a new geographical unit, the "Sub-service Areas" or SSAs. SSAs were closely associated with the area covered by a Gram Panchayat, so as to facilitate the relationship between financial inclusion and welfare programs, most of which are implemented through GPs. But, concern for the viability of BCs also led to a statement that each BC should cater to a population of about 5000-8000 (1000-1500 households), so that a SSA would sometimes encompass two or more GPs, while in other cases a GP could be divided into two SSAs.

Lead Banks were correspondingly asked to draw up a new set of "road maps" which placed each village within a SSA, and allocated a bank branch to each SSA to ensure coverage of all villages by either a BC or a physical branch. Building on the initial road map, the BCs who had been designated for a particular large village (2000 plus population) was now assigned to cover the associated SSA. The fact that the 2010 village-based approach pre-dated the 2011-12 area based approach therefore meant that of the set of unbanked villages in 2012, those that were placed in an SSA that included a village that had already been assigned a financial inclusion institutions (branch or BC) under the 2010 policy, were the first to be covered by a financial inclusion institution. That is, the geography of the GP that a village was located in determined the phasing of the program across all villages. Financial institutions were initially available to village located in GPs with a village of size 2000 or more, with the extension to SSAs with no such village planned to occur over the 2012-14 period.

The BC-led financial inclusion drive also gave new impetus for the opening of rural bank branches. Because BCs were required to be closely supervised and monitored by banks, a 2010 directive required a "base branch" to be identified for each BC. This branch would be responsible for oversight and monitoring of the BC's activities. The same directive stipulated that the base branch should be within a 30 km distance from the BC's area of operation.[8] This required an expansion of the bank branch network. Banks were asked to ensure that "brick and mortar" bank branches were available in all villages with a population of 10,000 or more by September 2012, with this cut-off being reduced to 5,000 in "underbanked" districts.[9]

From the start, the viability of BCs was a concern, and several studies validate such concerns. A study based on interviews of 11 leading Business Correspondent Network

[8] This "distance" criterion was dropped in 2014.

[9] An "underbanked" district is defined as one in which the average population per bank branch is less than the national average. 6 of Karnataka's 27 districts are underbanked.

Managers, reported average enrollments of 1,158 per agent. However, the number of transactions per agent per month were only 44, with an average value of Rs. 1,295 (MicroSave 2012). The average monthly commission of a BC was estimated to be Rs. 1,189. As a point of comparison, state-level wages for MNREGA were Rs. 155 in 2012-13. Thus, 8 days of work under the MNREGA program in 2012-13 would have generated the same monthly income as earned by a BC.

2.3 Welfare Policies

While improved access to formal financial services can directly enhance the welfare of the poor, the impetus for financial inclusion came in no small part from the desire to improve welfare programs, particularly India's largest such program, a public works work-fare program guaranteeing 100 days of employment to each rural household, called the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA). The Act came into effect in 2005, and was phased in over a two year period commencing in February 2006. By April 2008, it covered all districts of the country. In 2008, the government mandated that all MNREGA wage payments would be directly deposited in beneficiaries' bank or post office accounts. MNREGA guidelines called for banks (led by the district's Lead Bank) and GP members to ensure that bank accounts were opened for all who registered to work under the program, and that awareness and outreach activities were conducted to ensure their ability to manage savings accounts. By December 2009, 82% of MNREGA wages were being disbursed through bank or post office accounts,[10] with the importance of bank accounts relative to savings accounts varying across states. In Karnataka, MNREGA bank accounts have always dominated accounts at post offices; the latest data (2014-15) reveal that 90% of MNREGA accounts were with banks, with only 10% being at post offices.[11]

When the 2009 policy was announced, it was widely acknowledged that costs to rural households of transacting with banks were high, due to limited access to bank branches as well as the formality of bank transactions. Doorstep banking through BCs was believed to offer a solution, not just because of the reduced cost of access but also because of the help that they would offer households in handling financial transactions and in encouraging use of financial

[10] RBI Circular dated 4 march 2010.
[11] Data is from www.nrega.nic.in

accounts.[12] However, while branchless banking was viewed to be critical for the success of welfare programs, the potential impact of welfare programs on the financial viability of local banking agents was also widely recognized. The belief that India's high poverty rates renders rural financial institutions unviable is widely held. For example, the Report of the Committee on Financial Inclusion (2008) noted its belief that "many segments of the population… have a limited or weak demand for financial services." It went on to state that "merely pumping a backward region with financial capital is not going to be enough in the absence of improvements on the side of human, social and physical capital… In the absence of all this, merely insisting on financial inclusion will not work."

3. Data and Sample Statistics

The data for the empirical analysis of this paper combines household survey data with administrative data from several sources on financial services and financial service providers.

The household data comes from a survey I conducted, along with co-authors, for evaluating the effect of several educational initiatives in the state of Karnataka, in South India. Because the primary objective was to study schooling outcomes, we surveyed all households with children in grade 3 in 2009 in a set of 720 villages distributed over 360 Gram Panchayats in 11 districts of the state. School clusters, an administrative unit overseeing primary schools in the state, each covering approximately 3 Gram Panchayats, were selected using proportional random sampling from each district. Within each cluster, 1 Gram Panchayat was randomly selected in small clusters and 2 in larger clusters. Two schools were then selected from each Gram Panchayat. The main village school was always included, while the second school was randomly selected from amongst remaining schools.

The household survey provides information on income, expenditures and savings. Data is available for approximately 11,500 households from the baseline (2009) survey. The households were re-surveyed in February-March 2013. A significant effort was made to minimize attrition through a prolonged stay in survey villages at the time of the re-survey, resulting in a relatively low attrition rate over the four year period of 11%. The analysis of this paper uses data only for the set of households who were matched over both survey rounds. Removing observations with

[12] Because the disbursement of welfare benefits represented a significant proportion of a BC's transactions, the Government allows MNREGA funds to be used to cover the service charges of BCs for such transactions.

missing values, and trimming the data for observations in the bottom and top percentile results in a sample size of approximately 17,000 households over the two years. The sampling of households is not random; it under-represents richer households, since it samples only households whose children attended government schools. Data from the 2009-10 DISE (District Information System for Education) survey suggest that students enrolled in private elementary schools accounted for 16% of the student population.

The primary source of data on the availability of financial services is the financial inclusion "road map" data that all banks were required to submit at various points of time and that are then reported on the financial inclusion web site maintained by the State's Lead Bank. At the start of the 2010 financial inclusion policy, the lead bank identified all villages with a population of 2000 or more that were "unbanked" by either a bank branch or a BC. A status report at the end of 2013 provided a full listing of every village in the state (regardless of population), the identification of the Gram Panchayat it was associated with as well as the SSA it was assigned to, and information on coverage ("Existing" or "Proposed") and, if covered, the type of institution (BC or Branch) available. For all types of coverage, the name of the "financial inclusion" branch is also provided, as is the name of the BC, his or her mobile number, and other details verifying the appointment of the BC. Combining these two data sets, and merging them to our household data by village, information is available on the availability of financial services (by institution) in both survey years.

The data on "unbanked" villages in 2010 does not state the type of institution (BC or branch) available in banked villages. For this purpose, I used data from the Reserve Bank of India on all bank branches in the country. This listing provides the data at which each bank branch was opened. Matching this with all banked villages of population size 2000 and above, I am able to determine which villages were covered by a bank branch in 2009-10. I also match the household data set to data from the 2001 Census. While the financial inclusion data also provide a listing of all villages within a Gram Panchayat with their population size, and hence on the geography of each Gram Panchayat, the census also provides other information for all villages, such as the scheduled caste and tribe population in each village of each Gram Panchayat.

Summary statistics from the household survey are provided, by year, in table 1. These data document the significant increase in household incomes in the four years spanning the survey, and a matching increase in household savings and expenditure. Average household

income increased from Rs. 43,360 in 2009 to Rs. 84,563 in 2013. The data are consistent with the significant increase in state level income during this period, as revealed in aggregate state level data. In current Rupees, net state domestic product increased from Rs. 51,364 in 2009-10 to Rs. 84,709 in 2013-14. Similarly, the expenditure data correspond to official state-level figures. The state (expenditure) poverty line in 2009-10 for rural households was Rs. 629.4 per capita, suggesting annual household expenditure for a family of 5 at the poverty line of Rs. 37,764, with 34% of the rural population estimated as being below the poverty line. By comparison, the survey average level of household expenditure for this year of Rs. 40,954. Between the two survey years, the proportion of households reporting a savings account increased significantly, from 21% to 76%.

Table 1 also documents the insignificant reach of financial outlets in survey villages in 2009, and their substantial growth by 2013. Of our survey villages, only 13% had a bank branch (BR) in 2009, while only 4% were covered by a BC. By 2013, the percentage of villages covered by a BC had increased to 47%, while 24% reported coverage by a bank (with coverage in the second survey year implying the availability of a bank in the village's sub-service area).

Table 2 provides information on the geography of GPs. The average GP has a population of approximately 6,200, distributed over 7 villages. The small size of villages in the state is revealed in the average population of each village, of 2,601. 68% of GPs have a village with a population of 2000 or more, but only 12% contained a village with a population of 5000 or more, and only 2% had a village with a population in excess of 10,000.

Table 3 provides summary evidence on the effectiveness of policy rules. This table uses the village as a unit of analysis, examining the availability of BCs and bank branches in villages, by GP geography. Because the unit of analysis is the village, the data reflect the change in policy between 2009 and 2013. In 2013, rules dictated that a village was defined as being covered by a financial institution, if the financial institution was located within the SSA, not necessarily in the village itself. In contrast, 2009 availability is measured at the level of the village.

Reflecting the policy, the data reveals that the largest increase in the incidence of BCs between 2009 and 2013 occurred in previously unbanked GPs that included a village with a population of 2000 or more, with the proportion of villages in this category reporting coverage by BCs increasing from 9% to 68%. There was some growth in GPs with all villages below 2000, a consequence of the intent to phase in financial services to all SSAs following the initial

assignment of BCs only to SSAs with a village of size 2000 or more. However, due to the later introduction of BCs in such villages, this growth was much less (from zero to 39% by 2013).[13]

4. Theoretical Framework

The theoretical framework that underlies the empirical analysis of this paper is a standard dynamic model of household decision that also encompasses portfolio choice, as in MaCurdy (1999). I provide only a brief sketch here, highlighting factors specific to the Indian setting.

I assume that households' utility functions are defined over consumption and hours of work, both on family enterprises including the family farm (for households that own such enterprises) and on the unskilled wage labor market. The latter market includes the option of hours of work on the government's public work program. Within this framework, the availability of local financial outlets such as BCs can affect savings in a variety of ways.

First, they will reduce the transaction costs involved in opening and maintaining bank accounts. Second, building on the behavioral economics literature, the presence of local bank agents in the village can enhance the value that households place on future consumption relative to current, essentially acting as a time-dated preference shifter (Thaler and Shefrin 1981, Laibson 1997, Banerjee and Mullainathan 2010). That is, they may modify household behavior in the same way as a "planner" who helps individuals enhance self-control (Thaler and Shefrin 1981). To the extent that they modify preferences, any effect on savings need not be specific to a given asset. However, because BCs are explicitly charged with promoting household's use of financial institutions and savings accounts in particular, they are likely to most affect preferences for accumulating assets in financial institutions, specifically in savings accounts. Any effect on preferences, combined with any direct effect on the rate of return on savings accounts, perhaps due to households' beliefs regarding the safety of funds held in these accounts, operates like an increase in interest rates, shifting consumption from the current to future periods.

A third avenue whereby BCs may affect savings is through their effect on labor markets, a consequence of the tie-up between the government's financial inclusion program and its public

[13] It is worth noting that the set of financial inclusion policies in place in 2013 has been further changed. The new set of policies, announced by Prime Minister Modi in 2014, call for a household approach that ensures a bank account for every household.

works program, MNREGA. Utilizing a RCT in the state of Andhra Pradesh in India, Mullainathan et al (2014), show that the use of BCs and mobile technologies to deliver MNREGA payments is associated with improvements in the timeliness of wage payments as well as a reduction in the leakage of funds between the government and target beneficiaries. This effect, therefore, is similar to that of an increase in wages earned on the unskilled labor market. While this effect may initially be specific to those who gain employment under the MNREGA program, there are also likely to be general equilibrium effects that cause wages for all unskilled labor to increase. Through this, the tie-up with MNREGA may also affect the income of non-labor households, but the effect will likely be in the opposite direction, reflecting the negative effect on farm profits of wages for hired labor.

Maximization of household utility over the planning period, subject to period-specific preference shifters (including BCs and BRs), a budget constraint, equations determining wages and asset-specific interest rates, and time constraints generates equations for household, expenditure, income, accumulation of different assets, and so for household savings. A unique constraint on household behavior comes from the requirement that all households who seek employment in MNREGA must have a bank account. This implies that the decision to open a bank account is determined by the decision to participate in the public works program. It also separates the decision to open an account from the decision to accumulate savings in it. As in a standard portfolio choice model, accumulation of savings in a financial account will be based on a comparison of the (implied) rate of return to a savings account relative to that of other assets. Thus, even though BCs may increase the net return on financial assets, households may still choose not to augment their financial savings, despite any costs they may have incurred in opening bank accounts, if the net rate of return on financial savings is less than that on other assets.

The above framework ignores the profitability of the BC, a central concern in models of service delivery in local markets. When agents are limited to a specific geography, small market size, in conjunction with any fixed costs that the BC must bear, such as travel costs to a village, may imply that the BC realizes profits only from larger villages in which the number of transactions will remunerate him for his fixed costs. If so, the BC may not visit small villages at all, reducing his effect on the average household in the GP. If the number of financial

transactions increases with household wealth, then this model also suggests the potential for persistent poverty, since BCs will be most effective in relatively wealthy GPs.

This last finding may, however, be reversed because of the tie-up with MNREGA. The fact that BCs earn a commission when households withdraw (automatically deposited) MNREGA earnings implies that they may earn larger profits by serving poor households. While BCs may have to spend time with households and exert effort to convince them to utilize bank accounts, no such effort is required in earning commissions from the poor, who can only access their earnings by withdrawing them from their bank accounts. Even without the tie-up with MNREGA, however, BCs may earn greater profits from the poor relative to the non-poor because of the greater frequency of the income streams of the former. Wages on the casual labor market are typically paid weekly or bi-weekly. In contrast, farm incomes primarily accrue only twice or thrice a year, at the time of agricultural harvests.

In either case, consideration of BC effort and fixed transaction costs suggests the importance of allowing the effect of BCs on household savings to vary with variables that affect his or her profitability, particularly indicators of market size.

5. Empirical Model

This paper focuses on the effect of business correspondents on household savings, ignoring that of bank branches. As noted in the Introduction, the lion's share of growth in financial outlets in India after 2009 has been in the form of business correspondents, with far less growth in the number of bank branches. In our survey data, too, only 9% (12 out of 128) of the bank branches located in survey GPs were opened during the survey period of 2009-10 to 2012-13.[14]

5.1 Savings equation

The basic equation I use for inferring the effect of BCs is:

$$(1) \qquad S_{ijt} = \alpha_o + \alpha_1 BC_{jt} + \boldsymbol{X'_{it}\alpha_2} + u_{it}$$

[14] An additional 8 (6%) were built in 2013 and 2014.

In this equation BC_{jt} is an indicator variable that takes the value 1 if a BC is assigned to village j in period t. The coefficient on this variable reflects the effect of BCs on the rate of return to saving and, specifically, to financial savings. However, because of the tie-up with MNREGA, it may also include a wage effect. Because increased wages affect labor and non-labor households differentially, I separate the sample by land ownership, using inherited agricultural land for this purpose. By this definition, 44% of households are landless. I also report results that utilize an alternative definition based on the occupation that households report, in the baseline survey, as the primary source of income. Households that earn income primarily from the wage labor market for unskilled labor are classified as labor households (48% of sample households).

5.2 Identification

The change in the policy from the 2010 village based targeting to the 2011 geographic targeting of Sub-Service Areas implied moving from a targeted to a universal program covering all villages.[15] If this new policy had been fully implemented, then identification of the effect of BCs could only be through a before-and-after difference comparison between outcomes in the two surveys, and would likely not be credible. At the time of our end-line survey, however, the policy was far from being fully implemented, because of the time required to map all villages into SSAs and to assign BCs to each SSA. Because BCs had already been assigned to villages with a population of 2000 or more under the 2010 policy, the targeting rules of the 2010 policy defined the phasing in of the universal program: villages located in GPs that included a village that met the 2010 eligibility criterion were the first to be covered under the new policy, since the BC assigned to the eligible village was made responsible for covering all villages in the GP.

This well-defined phasing rule in conjunction with the availability of two rounds of data, including a baseline, suggests the use of a standard difference-in-difference estimator to evaluate the effects of the program. However, with incomplete compliance, this estimator recovers only ITT estimates. To recover causal estimates, I follow the standard practice of instrumenting the indicator variable BC by instruments suggested by the policy rules that dictate the phasing of program, in regressions that incorporate village fixed effects and year trends. That is, the difference-in-difference specification for the financial institutions represents the first stage

[15] The policy was changed again in 2014, to a new household based approach that requires ensuring that every household in India has a savings account.

regression, with the variables reflecting eligibility criterion constituting instruments for the second-stage identification of the effect of financial instruments on household outcomes.

Based on BC assignment rules, the variable that constitutes the basis for identification is an indicator variable that takes the value 1 if the GP included a village with a population of 2000 or more (*v_2000)*.[16] The actual instrumental variable I use is an interaction of a year 2 indicator with *v_2000*, so that identification comes from the fact that this policy rule was in operation only after 2009. As previously noted, all regressions include village and year fixed effects. To further ensure that identification is not through a non-linear effect of GP population, all regressions also include interactions of the Y2 indicator with a quadratic in village, GP and block population. I also allow for the presence of bank branches in a wider geography by including an interaction of Y2 with the block population per bank branch in 2009.

To account for the fact that the phasing-in of the policy required BCs to be first provided to unbanked GPs that satisfied this population criterion, I restrict the sample to those GPs without a bank branch in 2009. This reduces the number of GPs in the sample by 28% and the number of households by 30%. As previously discussed, the allocation of bank branches is primarily determined by village population, a variable that I include as a regressor. Because all regressions also include village fixed effects, it is unlikely that this selection will bias results. Restricting the sample in this way ensures the homogeneity of the group of villages that are not covered by a BC; if previously banked GPs are included in the analysis, then villages without access to a BC would include those who also lack access to bank branches, but also those with access to a bank branch (and without access to a GP).[17] Because policy rules implemented after 2009 also called for bank branches to be built in all villages with a population in excess of 10,000, I also restrict the sample to GPs in which all villages had a population of less than 10,000. This is an insignificant reduction in sample size of approximately 370 households.

The strength of the identification strategy comes from unique geographic targeting of the 2011 policy. Under this policy, the assignment of a particular financial inclusion institution to a

[16] I work with the geography of GPs, rather than SSAs, because the assignment to SSAs is endogenous, based on GP population. The intent of the policy was to coordinate financial inclusion plans with welfare programs. Because welfare programs operate through GPs, GPs were also taken as the basis for financial inclusion plans. SSAs were generally identified with a GP, except for GPs with very large populations that were divided into two or more SSAs.

[17] Alternatively, if the analysis includes previously banked GPs, then it would be necessary to also identify the effect of bank branches. This is more difficult, because of the relatively small growth in bank branches during the survey period.

village is based not on its *own* characteristics, but that of surrounding villages within the GP. This eligibility criterion is unique to the financial inclusion policy; India's welfare programs normally target individuals or households based on their poverty status, while policies that assign local public goods such as schools and health centers are based on habitation or village population size, not on the features of other villages in the GP. [18] While GP population and other characteristics can influence household outcomes, due to the GP being the administrative unit for all welfare programs and for the delivery of local public goods, such effects are more likely to be (linearly or non-linearly) continuous. Allowing for a continuous effect of GP and village population, it is unlikely that the specific economic geography cut-off that dictates the allocation of BCs, a population cut-off level that applies to the largest village in the GP, affects household outcomes through other channels.

5.3 Support for identification from falsification tests and different regression samples

Identification in standard difference-in-difference models is generally supported by examining whether growth rates in periods prior to the introduction of the program differ significantly across program and non-program villages. Lack of household data previous to the initiation of the financial inclusion policy precludes me from conducting such an analysis.[19] However, because policy rules dictated a cut-off level that divided GPs into those covered by BCs and those that were not, my identification methodology combines a regression discontinuity design with a difference estimator. Correspondingly, I provide support for the identification strategy by examining the predictive power of the policy cut-off, relative to other cut-off levels.

Specifically, I implement a set of falsification tests conducted on the first stage regression on the indicator variable BC, that test whether alternative village geographies also predict assignment, in regressions that condition on the set of geographies suggested by policy rules. For this, I construct the following set of indicator variables: *v_1000_2000* that takes the value 1 if the GP includes a village with a population of more than 1000, but no villages with a

[18] Welfare programs, though administered by the GP, generally target households depending on their poverty status (below or above a poverty line). And, most public goods are assigned on the basis of population, rather than the size distribution of villages. For example, the location of schools, is based on the population of a habitation (a sub-unit of a village), while health institutions are allocated on the basis of the population served per center. While the GP is the lowest administrative unit for almost all welfare programs, including MNREGA, allocations are generally based on the below-poverty-line population in each GP.

[19] Though other household data sets are available, including those provided by the National Sample Surveys, these data generally do not provide the village or GP identifiers required for this analysis.

population of 2000; *v_3000* that indicates a GP with a village of population size 3000 or more; and *v_4000* that similarly represents GPs with a village of size 4000 or more. In regressions on BC that include *y2* x *v_2000* (the policy indicator of whether the GP includes a village with population of 2000 or more) as well as interactions of *y2* with quadratics in village, GP and block population, I test for any additional effect of this auxiliary set of indicators. A lack of significance of these additional regressors supports the hypothesis that the placement of BCs does follow policy rules, and is not just a function of population size.

A second set of supportive regressions follows a standard approach in the regression discontinuity literature by restricting the sample to GPs with similar geographies. Evidence of a significant effect of the policy cut-off (*v_2000*), in both the first stage regressions on BC as well as in reduced form regressions on household savings, in similar GPs, suggests that the effect of the cut-off on savings reflects that of BCs. To define "similar" GPs, I consider the size of the largest village in the GP. Using this, I construct the following 4 "discontinuity samples": GPs with villages in which the maximum size of villages ranges from 5000 to 1000, from 4000 to 1000, and from 3000 to1000, and 3000 to 500.

5.4 Outcomes

I consider the effect of BCs on total household savings as well as on specific assets such as bank accounts, productive assets such as livestock and agricultural tools, and in gold. Additional insights on how BCs affect households comes from a set of auxiliary regressions that also considers their effect on household expenditure, wage and non-wage earnings[20], and on adult hours of work in the unskilled wage market as well as on family enterprises.

5.5 First stage and Estimating Equation

The first stage regression for the assignment of a BC to village j, in GP g, at time t, is:

$$(3) \qquad BC_{jt} = \rho_0 + \rho_1\left(y2 * v\_2000_g\right) + \rho_2 y2 + \rho_3\left(y2 * G_g\right) + \rho_4(y2 * V_j) + \rho_5\,(y2 * b) + \rho_6\, z_j + \rho_7(y2 * L_j) + \mu_v + v_{jt}$$

[20] While the primary source of non-wage earnings is own-farm cultivation, households, including labor households, also earn income from non-agricultural enterprises such as livestock.

In this equation, the indicator variable *v_2000* is as previously defined. μ_v represents a set of village fixed effects, while y2 is an indicator variable for the second survey year. G_g and V_j are GP and village level determinants, specifically a quadratic in GP and village population and village agricultural wages for men and women. The variable *b* includes a quadratic in block population and the (block) population per bank branch. z is a set of household level variables (indicator for scheduled caste or tribe, father's education, family size, number of adult males and females in 3 age groups, an indicator for whether the household inherited any agricultural land, and an indicator for whether the household reports the wage labor market as the primary source of household income in the baseline survey). Because I also report regression results that allow the coefficient on BC to vary across labor and non-labor households, defined by inherited land and primary occupation, equation (3) also includes both indicator variables for labor households (as components of the vector z_j) and their interaction with y2 ($y2*L_j$).

The basic estimating equation for outcome Y for household i in village j and year t is equivalent to (3), but includes the indicator variable BC, and excludes the instrumental variable *y2 * v_2000:*

$$(4) \qquad Y_{ijt} = \alpha_0 + \alpha_1 BC_{jt} + \alpha_2 y2 + \alpha_3 (y2 * G_g) + \alpha_4 (y\_2 * V_j) + \alpha_5 (y2 * b) + \alpha_6 z_{iJ} + \alpha_7 (y2 * L_j) + \mu_v + v_{jt}$$

In regressions that allow the coefficient of BC to vary by labor status, the interacted terms (*BC*labor, BC*non-labor*) are treated as endogenous. The instrumental variables in these regressions are the predicted value of BC from equation (3), interacted with the indicators for labor households.

5.6 Testing predictions of economic geography models

To test the predictions of models of the provision of non-tradeable services under fixed costs, I implement a set of regressions in which I interact the indicator variable BC with characteristics of the economic geography of the GP, and consider the effect of BC and the interacted term of household financial savings and other household outcomes. As before, all interactions with BC are treated as

endogenous, and interactions of the predicted value of BC with the set of augmented geographic variables are used as instruments.[21]

A first set of variables is intended to capture the effect of market size. As described in the previous section, the fact that a GP includes a number of villages suggests that the BC will make a decision on the profitability of visiting any given village based on village market size. I therefore include interactions of BC with village population and its square. To allow for the fact that poor households may constitute the primary source of earnings for BCs, I also include interactions of BC with the scheduled caste and tribe (SC/ST) population in the GP. The data set lacks other measures of poverty at the level of the GP. However, membership in scheduled castes and tribes is a well-known predictor of poverty. To ensure that the interaction with the GP SC/ST population does not merely reflect variation in the effect of BCs across SC/ST and other households, I also include an interaction of BC with an indicator that takes the value 1 if the household belongs to a scheduled caste or tribe.

A second set of variables considers whether aspects of the economic geography of the GP are also relevant. The hypothesis that fixed costs matter suggests that the BC may concentrate on the largest village, with coverage of other villages not being financially viable. I therefore construct an indicator variable that takes the value 1 for all "small" villages, defined as all villages other than the largest village in the GP, and include an interaction of this variable with BC. A second interaction is between BC and the number of villages in the GP. Commonly used measures of concentration, such as a Herfindahl Index calculated on the basis of the share of each village in the population of the Gram Panchayat, are closely correlated with the number of villages, with more villages corresponding to lower population concentrations. This indicator is preferred over the Herfindahl index because of the relatively small number of villages in many GPs; in such cases, the Herfindahl index loses explanatory power in regressions that also include the village population and its square. In a final set of regressions, I also additionally interact the indicator for "small" villages with the population of the largest village. This allows me to test if any disadvantage faced by smaller villages increases with the population of the largest village, again signifying that geographic concentrations affect service delivery.

6. Results

[21] In these regressions, the first stage regression on BC also includes interactions of y2 with the set of geographic variables.

6.1 First stage regressions, falsification tests and reduced form regressions

First stage regression results are in table 4. The first regression provides estimates of the effect of the instrument, *y2*v_2000*, on the indicator variable denoting assignment of a BC to the GP. I start with a basic set of additional regressors that control primarily for population at the village, GP and block level, but omit all household variables other than the indicator variable for inherited land and its interaction with y2.[22] All regressions include village fixed effects, and standard errors are clustered at the level of the village. This regression yields a positive and statistically significant effect of the interacted term, *y2*v_2000*, on coverage by a BC.

The remaining regressions in this table report results from falsification tests, as described in section 5.3. Regressions (2) through (4) test whether other economic geographies, defined by whether the GP includes a village of population size other than that dictated by the policy, also predict coverage by a BC in regressions that include the policy cut-off (*v_2000).* These regressions reveal that coverage by a BC is consistently predicted by whether the GP includes a village with a population size of 2000 or more. Conversely, all other cut-offs, including indicator variables for whether the GP only has smaller villages (of size 1000, but none of size 2000 or more) or slightly larger villages (with a population of 3000 or more) have considerably smaller effects on coverage by a BC. The magnitude of the coefficients on these alternative geographies is such that none are statistically significant at a 5% level. These regression results suggest that the policy cut-off correctly identifies coverage by a BC.

Additional support for the validity of policy rules in identifying coverage by a BC comes from regressions (5) through (8) in the same table. These regressions restrict the sample to narrower intervals around the policy cut-off, as described in section 5.3. Sample sizes are given at the bottom of the table. In all four regressions, the effect of *y2*v_2000*, remains statistically the same, and statistically significant, despite the reduction in sample size. This suggests that even when the sample is restricted to very similar GPs, who should also be similar in unobservable characteristics, the instrument *y2*v_2000* still has explanatory power in regressions on coverage by a BC.

Table 5 reproduces the regressions reported in table 4, but now using total household savings as the dependent variable. The regressions therefore are reduced-form regressions of savings on the instrument that again explore the sensitivity of results to different geographies and

[22] The set of additional regressors is described in section 5.5.

discontinuity samples. If BCs affect savings, then *y2*v_2000* should also predict household savings. And, a lack of significance of other geographies would suggest that this policy cut-off is a valid instrument for BC, in that it is only this geography that affects savings. If the significance of *y2*v_2000* in these second stage reduced form regressions was a consequence of a correlation with omitted determinants of savings, we could also expect closely similar geographies to similarly display such a correlation.

The results reported in columns (1) through (4) confirm the statistical significance of *y2*v_2000* in regressions on total household savings, as well as the lack of significance of alternative policy cut-offs. Additionally, the magnitude of the coefficient on *y2*v_2000* remains statistically the same in the regressions reported in columns (5) through (8) that restrict the regression sample to smaller intervals around the policy cut-off. However, the relatively small sample size in the last two regressions yield larger standard errors and hence coefficients that are only statistically significant at the 10% level.

Taken in combination with the results of table 4, these regressions support the identification strategy and also suggest that the program of branchless banking through BCs did increase savings.

6.2 OLS and IV regressions

Table 6 reports a first stage regression of BC on the full set of regressors used in the subsequent regressions on household savings, adding a set of household level variables to the set of village, GP and block level determinants of the previous table. It also reports the corresponding first stage regression of household savings on the full set of regressors, as well as results from OLS and IV regressions of savings on BC. The last column of this table reports results from an IV regression that includes a cubic term in both GP and village population, thereby testing the sensitivity of results to functional form. There is no significant difference in the IV estimates reported from this specification. Accordingly, subsequent regressions drop the cubic term, including only a quadratic term in GP and village population.

The OLS regression of household savings on BC suggests a negative effect of coverage by a BC on household savings. In contrast, the IV regression, supporting results from the reduced form regressions of the previous table, yields a positive and statistically significant effect of the assignment of a BC to a set of villages on household savings. These regressions suggest a

downward bias in OLS regressions. This in turn may be because BCs were introduced in relatively larger villages, with perhaps better infrastructure, and so lower growth rates as compared to other villages that may have experienced faster growth due to greater investments in infrastructure. The use of a policy cut-off distinguishes between broad correlations with population of the type described above.

The estimates suggest that coverage by a BC increases annual household savings by approximately Rs. 15,500. While it is difficult to compare this magnitude with that from previous research, other authors also note a large effect of access to financial services on households. Prina (2013) finds that access to a savings account increased monetary assets by more than 50%, and total assets (monetary plus consumer durables and livestock) by 16%. Burgess and Pande's (2005) research suggests that opening a bank branch in an additional rural location per 100,000 persons lowers aggregate poverty by 4.1 percentage points. In rural Karnataka, the population per bank branch at the initiation of the BC-led financial inclusion drive (2010-11) was 19,205.19. If population per banking outlet is taken as an indicator of access to financial outlets, the provision of a BC in a village generated a huge improvement in access, more than tripling the number of outlets per thousand population, from an average of 19,205 to approximately 6000 (average GP population in our survey data).

6.3 Effect of BC on savings by asset type, income, expenditure, and occupation

The next two tables report the coefficient on BC from regressions for savings in different types of assets (table 7) as well as from regressions on non-wage and wage earnings, household expenditure, and (adult) male and female hours of work (table 8).[23] Both tables also include results from regressions that allow the coefficient on BC to vary with the indicators of labor market dependence previously described (reported primary occupation and inherited land). The interaction of BC with household type is treated as endogenous, as described in section 5.6. Columns (4) and (7) test the equality of the coefficient on BC across labor and non-labor households for each of these two classifications.

The results are very similar across both classifications. They suggest that BCs have a larger effect on the total savings of labor households relative to non-labor households, with the

[23] The types of assets included in this table is not exhaustive. Our survey did not collect details on investments in agricultural machinery, non-farm capital, improvements in land and other capital, or housing.

difference being statistically significant at the 5% level. Both types of households also report an increase in savings in bank accounts, with this increase being slightly larger for non-labor households. Using primary occupation to distinguish between the two types of households, the equality of the coefficient on BC in the regression on financial savings is rejected at the 5% level. A similar test rejects equality of coefficient only at the 17% level when households are distinguished by inherited land. The smaller effect of BCs on the total savings of non-labor households appears to be because saving in bank accounts crowds out saving in gold; the coefficient on BC in regressions in which the dependent variable is savings in gold is negative and statistically significant for non-labor households. Though coefficient magnitudes are similar for labor households, they are statistically insignificant at conventional levels. There may also have been additional crowding out on other forms of savings not collected as part of the survey, such as cash-in-hand, home construction and improvements, or investments in other agricultural and non-agricultural assets.

The regression results reported in table 8 provide evidence on how households increase savings in response to access to a BC, thereby explaining differences in the effect of BCs on labor and non-labor households. As in table 7, I present results that allow the coefficient on BC to vary by the household's (reported) primary source of income as well as by landownership.

The results suggest that BCs cause reductions in the household expenditure of both labor and non-labor households, indicative of a shifting of expenditure from the current to future periods. This reduction could be a consequence of an effect of BCs on households' preference for savings or an increase in the rate of return to savings (equivalently, a reduction in the relative price of future consumption). The magnitude of the reduction in expenditure induced by BCs appears to be equivalent across labor and non-labor households; it is not possible to reject the hypothesis of equal coefficients at conventional levels of significance.

Thus, effects on household expenditure cannot explain the larger effect of BCs on household savings. Instead, the regressions reported in table 8 reveal that this is a consequence of the larger effect of BCs on the wage earnings of labor households. The results reveal a statistically significant effect of BCs on the wage income of labor households, with the difference in this effect across labor and non-labor households being statistically significant, at a 1% level, under both classification systems. Moreover, when households are classified by primary occupation, the increase in wage income is greater for female members of the household

than for males. In contrast, the effect of BCs on non-wage earnings from own enterprise (both agricultural and non-agricultural) is negative and not statistically significant at conventional levels.

Further support for the hypothesis that BCs affect the return from wage labor market participation comes from regressions that examine the effect of BCs on hours of work of the prime-age male and female in the household in family enterprises. I distinguish between hours of work on family enterprises and in the unskilled wage labor market. Family enterprises, in turn, include both agricultural and non-agricultural businesses such as livestock. Because data on the hours of work of the prime-age father and mother in the household was collected independently of data on earnings, this provides an independent test of the effect of BCs on hours of work in different markets.[24]

Results from regressions on hours of work are reported in the bottom rows of table 8. BCs increased hours of work on the wage labor market for both men and women in labor households, and also, to a lesser extent, female hours of work in this market for non-labor households. The difference in hours of work in the wage labor market across labor and non-labor households is statistically significant at conventional levels. In contrast, hours of work in family enterprises decreased for both men and women in non-labor households (across both classification systems), with these decreases being statistically significant when households are classified by primary occupation. Labor households, too, report a decline in hours of work in own enterprises when households are classified by primary occupation, with the decline being statistically significant for male labor.

This difference in the effect of BC on wage and non-wage earnings suggests an effect through MNREGA. Higher MNREGA wages, particularly for women, would increase hours of work in MNREGA projects but also increase wages, and hence hours of work, in the (non-MNREGA) market for unskilled labor. For farmers who hire labor, this is likely to reduce the profitability of own-farm operations and cause a shift in hours form own-enterprises to the wage market. Alternative explanations for the decline in own-enterprise hours and increase in wage labor would have to require a negative effect of coverage by BCs on own-farm productivity. However, I am not able to test this hypothesis directly, since data on households' MNREGA earnings or participation in the MNREGA program are not available.

[24] In contrast, wage earnings include earnings to other family members as well.

It is worth noting that the larger effect of BCs on the total savings of labor relative to non-labor households is not matched by a similarly larger effect on financial savings. To the extent that the increase in wage earnings made possible by BCs represent increases in MNREGA earnings that are directly credited to bank accounts, the results suggest that households withdraw these earnings and hold them in other assets, such as grain inventories.

A final result worth commenting on is the effect of BCs on education and health expenditure (also reported in table 8). While I find no significant effect of BCs on health expenditures, the results reveal statistically significant effects of BCs on educational expenditures, but only in labor households. The difference between labor and non-labor households in this regard is statistically significant at the 1% level when households are classified by land ownership, and at the 13% level when classified by primary occupation.

6.4 Heterogeneity in results by GP geography and village population

Tables 9 provides evidence on whether the effect of BCs on households varies with village population and with the economic geography of GPS, using the set of interacted variables described in the previous section. Table 10 differs from table 9 only in that it further refines the effect of "small" villages on household outcomes, allowing this to vary not just by BC coverage, but also by the size of the largest village in the GP. Thus, the effect varies with an increase in the concentration of population within the GP.

The first column presents results from a regression in which the dependent variable is the total savings of households. This regression suggests that greater geographic concentration increases the effect of BCs on savings, as predicted by theoretical models. The effect of BCs on total savings is smaller in "small" villages relative to the largest village in the GP. And, an increase in the number of villages in the GP, and hence a reduction in the extent of concentration, reduces the coefficient on BCs. The same regression also reports a positive coefficient on the interaction of BC with the population of the village in which the household resides, though the effect tapers off at very high populations. Again, this supports the theory that market size affects the efficiency of local services. Poverty, as reflected in the size of the SC/ST population in the village, matters less, suggesting that it is the non-poor population that determines the effectiveness of BCs. Tests of the joint significance of the interaction of BC with

the quadratic in village population and, separately, the quadratic in the SC/ST population are provided in the bottom rows of the table.

Regressions on expenditure and earnings are again useful in understanding how the effect on savings are realized, and the specific role of wage labor markets. The greater effect of BCs in more concentrated GPS appears to be largely a consequence of their effect on expenditures and non-wage earnings. For example, the results suggest that BCs increase consumption in smaller villages relative to the largest village, thereby reducing total savings in the former set of villages.

In contrast, effects through wage earnings appear to favor GPs with less population concentration and higher levels of poverty. Thus, the effect of BCs on male wage earnings is greater in smaller villages relative to the largest one, and in GPs with a larger number of villages. And, while the coefficient on BC in regressions on male wage and non-wage earnings increases with the population of the village in which the household is resident, interactions with the SC/ST population matter only in regressions on female wage earnings. BCs have a larger effect on female wage earnings in villages with a larger SC/ST population.

The results in table 10 are similar to those in table 9. They do, however, provide greater support for the hypothesis that geographic concentrations matter. The results suggest that, as the size of the largest village in the GP increases, BCs have less of an effect on the savings of households in smaller villages.

In interpreting these results, I emphasize again that these regressions only provide suggestive evidence; the same pattern of interactions, for example, may result from causes other than those of the effect of economic geography on the provision of local services. However, they are broadly consistent with models which suggest that the provision of local services under decreasing average costs will result in greater provision in larger villages and in areas with greater population concentrations. And, the finding that village poverty mediates the effect of BCs only for female wage earnings is again suggestive of a link with MNREGA. Other than through female wage earnings, the provision of BCs affects household savings more in villages with a larger non-poor population.

Our results emphasize an important source of inequality as a consequence of the local provision of financial services. They suggest that households located in more concentrated geographies, and in larger villages, are better served by BCs, despite the intent of the program to offer coverage to all households. While the tie-up with welfare programs reduces this effect, the

results also suggest differences in the effect on poor households depending on their location. That is, larger benefits accrue to labor households who reside in village with a larger poor population.

7. Conclusion

The research of this paper provides evidence on the effectiveness of India's recent financial inclusion drive on the savings and other outcomes of rural households in the state of Karnataka, India. As with other recent policy initiatives in many developing economies, this policy is believed to have significant potential to enhance the welfare of the poor. This is primarily because of its use of mobile technology to essentially deliver financial services at the doorstep of households, but also because of its use of local agents to encourage savings and facilitate financial transactions. The potential of the Indian policy is even larger, because the government requires benefits from its primary welfare program, a work-fare program known as MNREGA, to be deposited directly in households' bank accounts, thus providing households with a strong motivation to open savings accounts.

Using a unique data set that matches two rounds of household data, over a period spanning the phasing-in of the financial inclusion program, with rich data on the availability of financial institutions at the level of the village, I identify the effect of financial institutions, exploiting both the variation in access over years, but also the eligibility rules that determined the phasing of the program across villages on the basis of population cut-off levels that applied to the largest village in the GP.

Separating households into labor and non-labor households I find that the availability of BCs did increase household savings, particularly for labor households. Additional regressions on expenditure and income suggest that this difference is largely because of the effect of BCs on wage earnings. The fact that the increase in savings in bank accounts is far less than the increase in wage earnings suggests that households choose to hold additional savings in other assets, even though the MNREGA portion of wage earnings is directly deposited in savings accounts.

I also show that the effect of BCs on total savings is greater in the largest village in the GP, increases with geographic concentration within the GP, and increases with the size of the village population. These results suggest that the use of a business model that favors the local provision of financial services may exacerbate geographical and hence regional inequalities,

favoring households located in larger agglomerations. My results also show that the impact through (female) wage earnings is a counteracting force, resulting in a greater effect of BCs on household savings in villages with a large poor population. Thus, an increased tie-up of financial providers with other government programs that deliver benefits to the poor, such as subsidies, pension payments and the provision of other welfare entitlements (such as subsidized food grains), may further serve to counteract any adverse effects on inequality.

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Table 1: Summary Statistics, full sample by year

Variable	2009	2013
Savings	2,398.7 (55,729.5)	27,225.1 (70,746.9)
Income	43,359.5 (54,948.3)	84,563.1 (75,860-2)
Expenditure	40,954.0 (26,262.24)	57,265.0 (22,265.7)
Wage income		
Savings in Bk accounts	81.0 (7231.3)	4350.7 (11,815.2)
Prop of hholds reporting bank accounts	0.21 (0.41)	0.76 (0.42)
Prop. SC/ST	0.35 (0.48)	--
Father educ years	4.42 (4.67)	--
Mother educ years	3.33 (3.95)	--
Family size	5.72 (2.05)	5.66 (2.08)
Proportion of villages covered by financial outlets		
BC	0.04 (0.20)	0.47 (0.50)
Branch	0.13 (0.33)	0.24 (0.43)

Note: Survey data. Sample size is 10,229 in each year. Figures in parentheses are standard deviations.

Table 2: GP geographies

GP characteristics	2009
Average Population	6176.57 (2252.08)
Prop SC/ST	0.41 (0.45)
Number of villages per GP	6.74 (4.19)
Average population per village	2601.04 (2299.12)
Prop of GPs with a village >=2000	0.68 (0.47)
Prop of GPs with a village>=5000	0.12 (0.32)
Prop of GPs with a village>=10,000	0.02 (0.14)

Note: Sample size 379 (unit of analysis is GP). Figures in parentheses are standard deviations.

Table 3: Coverage of villages by BC and branch, by GP geography and year

GP geographical type in which the village is located	Covered by a BC		Covered by a bank branch	
	2009	2013	2009	2013
GP with all villages <2000 pop	0	0.39 (0.49)	0.06 (0.24)	0.07 (0.25)
GP with at least one village >=2000	0.07 (0.25)	0.50 (0.50)	0.16 (0.37)	0.32 (0.47)
Of which:				
GPs without bank branch in 2009	0.09 (0.25)	0.68 (0.47)	--	0.12 (0.33)
GPs with a bank branch in 2009	0.02 (0.15)	0.16 (0.50)	0.45 (0.50)	0.68 (0.47)

Note: unit of analysis is the village. Figures in parentheses are standard deviations.

Table 4: First Stage Regressions on BC, with falsification tests
(Dependent variable: BC)

	Sensitivity to different cut-offs				Discontinuity sample 1 5000-1000	Discontinuity sample 2 4000-1000	Discontinuity Sample 3 3000-1000	Discontinuity Sample 4 3000-500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y2 x v_2000	0.30*	0.34*	0.34*	0.34*	0.33*	0.35*	0.29*	0.32*
	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)
Y2 x v_1000_2000		0.09	0.10	0.09	--	--	--	--
		(0.10)	(0.10)	(0.10)				
Y2 x v_3000	--	--	0.02	--	--	--	--	--
			(0.09)					
Y2 x v_4000	--	--	--	-0.10	--	--	--	--
				(0.11)				
	--							
Y2	0.41	0.38	0.40	0.33	0.31	0.56	-0.53	-0.59
	(0.71)	(0.71)	(0.69)	(0.71)	(0.84)	(0.86)	(0.97)	(0.87)
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Y2 x square in GP and village population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regression F	40.79	38.64	36.46	36.14	33.03	37.78	30.53	37.35
(Prob > F)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sample size	13,054	13,054	13,054	13,054	10,926	9,259	7,498	8,489

Note: all standard errors are clustered at the level of the village. Additional regressors include interactions of Y2 with the following variables: block population per bank (2009), block population and population square, male and female agricultural wages, indicator variable for inherited agricultural land and its interaction with Y2. Regression sample excludes GPs with a bank branch in 2009 and GPs with a village with population >10,000. Discontinuity samples are based on the size of the largest village in the GP, in the following ranges: 5000-1000, 4000-1000, 3000-1000 and 3000-500. *Significant at 5% significance level +Significant at 10% significance level

Table 5: Reduced form regressions
(Dependent variable: Household savings, Rs. '000)

	Sensitivity to different cut-offs				Discontinuity sample 1 5000-1000	Discontinuity sample 2 4000-1000	Discontinuity Sample 3 3000-1000	Discontinuity Sample 4 3000-500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y2 x v_2000	5.39*	7.09*	6.84*	6.99*	5.86*	5.32*	5.14+	5.14+
	(2.57)	(2.74)	(2.82)	(2.74)	(2.71)	(2.75)	(3.07)	(2.87)
Y2 x v_1000_2000	--	4.63	4.75	4.41	--	--	--	--
		(3.64)	(3.64)	(3.65)				
Y2 x v_3000	--	--	1.73	--	--	--	--	--
			(3.02)					
Y2 x v_4000	--	--	--	-4.51	--	--	--	--
				(3.71)				
Y2	-42.32+	-43.90*	-42.01+	-46.12*	-28.99	-54.53*	-58.56+	-68.18
	(23.17)	(22.86)	(23.21)	(22.29)	(27.97)	(27.10)	(34.23)	(30.63)
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Y2 x square in GP and village population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regression F	59.58	57.60	56.77	52.98	52.33	48.45	36.47	40.34
(Prob > F)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sample size	13,054	13,054	13,054	13,054	10,926	9,259	7,498	8,489

Note: all standard errors are clustered at the level of the village. Additional regressors are listed in the note to table 4. Regression sample excludes GPs with a bank branch in 2009 and GPs with a village with population >10,000. Discontinuity samples are based on the size of the largest village in the GP, in the following ranges: 5000-1000, 4000-1000, 3000-1000 and 3000-500.

*Significant at 5% significance level +Significant at 10% significance level

Table 6: First stage, reduced form and IV regressions

	Dependent variable				
	BC	Savings (OLS)	Savings (OLS)	Savings (IV)	Savings (IV)
Y2 x v_2000	0.31*	4.72*	--	--	--
	(0.01)	(1.74)			
BC	--	--	-2.26*	15.46*	15.43*
			(1.05)	(5.76)	(5.60)
Y2	0.41*	-45.43*	-42.28	-51.82*	-62.39*
	(0.11)	(12.83)	(12.82)	(13.32)	(19.06)
Y2 x GP population ('00s)	-0.03*	-0.19	-0.15	0.24	0.67
	(0.001)	(0.18)	(0.17)	(0.22)	(0.67)
Y2 x GP population square	0.0002*	0.002+	0.002+	-0.0003	-0.01
	(0.00001)	(0.001)	(0.001)	(0.002)	(0.01)
Y2 x GP population cubed	--	--	--	--	0.00003
					(0.0001)
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Additional household regressors	Yes	Yes	Yes	Yes	Yes
Wald χ^2 (IV)/ Regression F (OLS) (Prob > F)	540.18 (0.00)	85.33 (0.00)	85.21 (0.00)	3699.75 (0.00)	3700.76 (0.00)
Sample size	13,054	13,054	13,054	13,054	13,054

Note: Additional regressors include a quadratic in village and block population, block population per bank, indicator variable for labor household (primary occupation is labor) and inheritance of agricultural land, interactions of Y2 with previous two indicators, interactions of Y2 with male and female village wages, scheduled caste/tribe indicator, father's education years, father literacy indicator, family size, number of household adult males and females in 3 age groups.

*Significant at 5% significance level
+Significant at 10% significance level

Table 7: IV estimates of effect of BC on Savings, by saving type, by primary occupation

		By primary occupation			By inherited land status		
	BC	BC * non-labor household	BC * labor household	X^2 test of equality of coefficients	BC*landowner	BC*landless	X^2 test of equality of coefficients
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Savings (Rs. '000)	15.46*	10.98+	23.82*	6.79	12.07*	25.46*	5.35
	(5.76)	(5.80)	(7.02)	(0.01)	(5.56)	(8.14)	(0.02)
Savings in (Rs. '000) by type							
Bank account	3.47*	4.13*	2.24+	3.89	3.86*	2.33	1.86
	(1.13)	(1.13)	(1.37)	(0.05)	(1.08)	(1.58)	(0.17)
Livestock	-0.23	-0.09	-0.49	0.83	-0.04	-0.79	2.07
	(0.52)	(0.52)	(0.63)	(0.36)	(0.50)	(0.73)	(0.15)
Ag. Tools	0.78	0.74	0.87	0.10	0.82	0.67	0.09
	(0.48)	(0.48)	(0.59)	(0.75)	(0.46)	(0.68)	(0.76)
Gold	-1.22	-1.24*	-1.19	0.00	-1.58*	-0.17	1.49
	(1.15)	(1.15)	(1.39)	(0.96)	(1.10)	(1.62)	(0.22)
Grain inventories	1.13	1.16	1.07	0.01	0.66	2.52*	1.55
	(1.49)	(1.49)	(1.80)	(0.94)	(1.43)	(2.09)	(0.21)
Sample size	13,054	13,054	13,054		13,054	13,054	

Note: Dependent variable is coefficient on BC, with standard errors in parentheses. All regressions include the regressors noted in table 6 as well as village fixed effects and interactions of Y2 with a quadratic in village and GP population. Omitted forms of savings are cash-in-hand and assets in non-agricultural family enterprise, land & home improvements, and new construction.

*Significant at 5% level

+Significant at 10% level

Table 8: IV estimates of effect of BC on Savings, Expenditure, Income and Family Hours of work

		Coefficients by primary occupation			Coefficient by inherited land status		
	BC	BC * non-labor household	BC * labor household	X^2 Test equality of coefficients	BC*landowner	BC*landless	X^2 Test equality of coefficients
Household non-wage earnings (Rs. '000)	-5.01 (5.81)	-5.19 (5.82)	-4.68 (7.04)	0.01 (0.92)	-4.63 (5.58)	-6.14 (8.17)	0.07 (0.79)
Household wage earnings (Rs. '000)	5.85 (4.73)	1.66 (4.75)	13.68* (5.76)	8.85 (0.00)	0.90 (4.58)	20.46* (6.70)	16.83 (0.00)
Household male wage earnings (Rs. '000)	1.94 (4.03)	-0.27 (4.04)	6.07 (4.89)	3.42 (0.06)	-1.80 (3.89)	12.98* (5.69)	13.30 (0.00)
Household female wage earnings (Rs. '000)	3.91* (1.82)	1.93 (1.83)	7.60* (2.22)	13.25 (0.00)	2.70 (1.76)	7.48* (2.57)	6.85 (0.01)
Household Expenditure (Rs. '000)	-14.62* (3.09)	-14.51* (3.10)	-14.82* (3.75)	0.01 (0.91)	-15.79* (2.97)	-11.15* (4.34)	2.26 (0.13)
Education expenditure	0.94 (0.58)	0.68 (0.58)	1.43* (0.70)	2.33 (0.13)	0.24 (0.57)	3.00* (0.83)	21.86 (0.00)
Health Expenditure	0.34 (0.48)	0.33 (0.48)	0.35 (0.59)	0.00 (0.97)	0.17 (0.47)	0.84 (0.68)	1.92 (0.17)
Annual hours of work ('00 hours)							
Father – wage labor market	4.82* (2.14)	3.39 (2.14)	7.49* (2.60)	5.05 (0.02)	3.54+ (2.06)	8.58* (3.02)	5.51 (0.02)
Male – own-enterprise	-2.31 (1.51)	-2.06 (1.51)	-2.77 (1.83)	0.31 (0.58)	-2.03 (1.45)	-3.14 (2.12)	0.54 (0.46)
Mother –wage labor market	5.42* (2.13)	3.71+ (2.14)	8.60* (2.59)	7.23 (0.01)	4.56* (2.05)	7.96* (3.00)	2.55 (0.11)
Mother – own enterprise	-1.33 (1.14)	-1.88+ (1.14)	-0.30 (1.38)	2.67 (0.10)	-2.07+ (1.10)	0.86 (1.60)	6.56 (0.01)

Note: Standard errors in parentheses. All regressions include the regressors noted in table 6. *Significant at 5% level +Significant at 10% level

Table 9 : Heterogeneity in effect of BC - 1

Regression coefficient on:	Total savings	Household Expenditure	Male wage earnings	Female wage earnings	Non-wage earnings
	(1)	(2)	(3)	(4)	(5)
BC	-17.65	-60.30*	-29.37*	3.59	-52.17*
	(15.71)	(8.08)	(10.43)	(4.64)	(16.28)
BC * SCST	0.61	-11.25*	-1.08	4.02*	-13.58*
	(5.92)	(3.04)	(3.93)	(1.75)	(6.13)
BC * smaller village	-17.43*	21.18*	11.65*	-2.91	-4.99
	(7.70)	(3.96)	(5.11)	(2.28)	(7.98)
BC * number of villages	-0.12	1.21*	1.20*	0.07	-0.18
	(0.72)	(0.37)	(0.48)	(0.21)	(0.74)
BC * village pop ('00)	3.25*	3.18*	1.49*	-0.37	5.31*
	(1.10)	(0.57)	(0.73)	(0.33)	(1.15)
BC * village pop sq	-0.02*	-0.02*	-0.01	0.001	-0.04*
	(0.01)	(0.01)	(0.01)	(0.003)	(0.01)
BC * village SCST pop ('00)	0.94	0.31	-0.07	1.67*	-0.35
	(1.56)	(0.80)	(1.04)	(0.46)	(1.62)
BC * village SCST pop square	-0.15*	-0.06+	-0.06	-0.06*	-0.09
	(0.07)	(0.03)	(0.04)	(0.02)	(0.07)
χ^2 test village pop	9.36	34.63	7.42	3.92	22.54
(Prob > χ^2)	(0.01)	(0.00)	(0.02)	(0.14)	(0.00)
χ^2 Test village SC/ST pop (Prob > χ^2)	0.45	0.20	0.00	13.11	0.02
	(0.50)	(0.05)	(0.99)	(0.00)	(0.88)
Regression Wald χ^2	3299.26	96,747.32	13,898.59	9462.40	13,971.58
(Prob > χ^2)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: BC and all interactions with BC are treated as endogenous, and instrumented by interactions of predicted BC from a first stage regression with the relevant interaction terms. All regressions also include interactions of Y2 with all the variables that are interacted with BC (village population and its square, village SC/ST population and its square, indicator for smaller village, number of villages in the GP, and indicator for household's caste), as well as additional regressors listed in the note to Table XXX. "Smaller village" is an indicator variable that takes the value 1 for all villages other than the largest village in the GP. Standard errors in parentheses.

*Significant at 5% level +Significant at 10% level.

Table 10: Heterogeneity in effect of BC - 2

Regression coefficient on:	Total savings	Household Expenditure	Male wage earnings	Female wage earnings	Non-wage earnings
	(1)	(2)	(3)	(4)	(5)
BC	-27.02	-56.40*	-22.74*	3.13	-63.81*
	(17.26)	(8.77)	(11.42)	(5.07)	(17.87)
BC * SCST	0.46	-10.83*	-0.94	4.12*	-13.54*
	(5.94)	(3.02)	(3.93)	(1.75)	(6.15)
BC * smaller village	11.89	6.71	0.73	-3.89	21.77
	(15.31)	(7.77)	(10.13)	(4.50)	(15.85)
BC * smaller village * population of largest village	-0.01*	0.005*	0.004	0.00	-0.01*
	(0.005)	(0.002)	(0.003)	(0.00)	(0.005)
BC * number of villages	-0.51	1.45*	1.29*	0.10	-0.45
	(0.73)	(0.37)	(0.48)	(0.21)	(0.76)
BC * village pop ('00)	3.54*	3.01*	1.30+	-0.37	5.63*
	(1.12)	(0.57)	(0.74)	(0.33)	(1.16)
BC * village pop sq	-0.03*	-0.02*	-0.01	0.001	-0.04*
	(0.01)	(0.01)	(0.01)	(0.003)	(0.01)
BC * village SCST pop ('00)	2.17	0.39	-0.50	1.62*	0.66
	(1.75)	(0.89)	(1.16)	(0.51)	(1.81)
BC * village SCST pop square	-0.18*	-0.04	-0.05	-0.05*	-0.11
	(0.07)	(0.04)	(0.05)	(0.02)	(0.07)
χ^2 test village pop	10.59	30.55	5.71	3.62	24.39
(Prob > χ^2)	(0.01)	(0.00)	(0.06)	(0.16)	(0.00)
χ^2 Test village SC/ST pop	1.69	0.15	0.14	9.85	0.17
(Prob > χ^2)	(0.19)	(0.70)	(0.71)	(0.00)	(0.68)
Regression Wald χ^2	3275.58	98,366.2	13,882.69	9485.18	13,885.17
(Prob > χ^2)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: BC and all interactions with BC are treated as endogenous, and instrumented by interactions of predicted BC from a first stage regression with the relevant interaction terms. All regressions also include interactions of Y2 with all the variables that are interacted with BC (village population and its square, village SC/ST population and its square, indicator for smaller village, number of villages in the GP, and indicator for household's caste), as well as additional regressors listed in the note to Table XXX. "Smaller village" is an indicator variable that takes the value 1 for all villages other than the largest village in the GP. Standard errors in parentheses.

*Significant at 5% level +Significant at 10% level.