Be the Best!: Do SMS Reminders Improve Banking Agent Performance in Rural India? *

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Abstract

We use three randomized experiments to test whether sending behaviorally-informed SMS reminders to banking agents improves their work performance. In particular, we measure the effect of these reminders on agents' efforts at enrolling customers into government pension and insurance programs in India. The first randomized experiment, with 3,120 banking agents, focused on increasing enrollments in the government's pension program using three behavioural framings: appealing to the agents' personal motivation, appealing to their prosocial motivation, and threatening that their performance was being closely monitored. We sent these messages either once or thrice a week. We find that sending SMS reminders thrice a week over a 4-week period threatening monitoring leads to an average increase of 13.4% in pension enrollments per agent, an effect that persists two months after we stop sending messages. We used these results to design the other two experiments, with 3,398 and 1,776 agents working with two banks, to increase enrollment in the government's insurance programs. SMS reminders increased enrollment in insurance products too, but only for agents working with one of the two partner banks. This bank is known for its commitment to financial inclusion. Overall, our results suggest that SMS reminders can be a cost-effective way to motivate agent performance, but only within a supportive ecosystem.

Keywords: pension, financial inclusion, behavioral economics, banking agents, CICO, India, RCT, SMS reminders

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1. Introduction

A healthy financial system is correlated with higher GDP and better economic conditions (Ogden 2019). In particular, recent evidence suggests that access to bank accounts, formal savings, and pensions can help households smooth consumption over time and manage unforeseen shocks (Kaushal 2014; Moore et al. 2019). While indicators related to financial inclusion have shown substantial improvements over the last decade[1], much remains to be done. For example, only 16% of adults report saving for old age in developing countries (Demirguc-Kunt et al. 2018). In India, where 88% of the workforce was in the unorganized sector in 2011-2012 (Narayana 2019) with no employer-sponsored benefits, only 12% of working adults are covered under any pension program (OECD 2017). Low- and middle-income countries like India still face many challenges to ensure that people are able to participate fully in the formal financial system and access useful products like savings accounts, pensions, and insurance.

A major constraint to accessing financial services is the scarcity of bank branches in rural areas. To address this gap, several countries have experimented with Cash-In, Cash-out (CICO) agents, a model also known as the "banking agent" model. In this model, banks partner with an agent network company to hire and manage local micro-entrepreneurs like shopkeepers. These "banking agents" act as intermediaries between customers and the bank, offering basic banking services at their retail points (Mehrotra et al. 2018). But while banking agents provide a crucial link to the formal financial system, their operations may give rise to principal-agent problems, especially since banks and agent network companies have limited abilities to monitor agent performance. Agents might not be intrinsically motivated to do their job, or could face various opportunities to engage in fraud. Mudiri (2013), for example, identifies "imposition of unauthorized charges on customers" as a type of fraud that occurs with high frequency. Given the key role of banking agents in increasing financial inclusion, understanding how to improve the way they provide banking services is important.

In this paper, we evaluate one such intervention to improve the performance of banking agents. In particular, we use three RCTs to test whether sending behaviorally-informed SMS reminders to banking agents increases the number of customers they enroll in a pension and two insurance products designed by the Government of India - the *Atal Pension Yojana (APY)*, the *Pradhan Mantri Jeevan Jyoti Bima Yojana (PMJJBY)* and the *Pradhan Mantri Suraksha Bima Yojana (PMSBY)*.[2] In our first RCT, we measure the marginal impact of SMS reminders on pension enrollment for agents associated with a bank known for its supportive culture, Bank 1. We partnered with a large agent network company that conducted a contest during the entire month of June 2019 to incentivize Bank 1 agents to increase pension enrollments. This contest offered different prizes to agents depending on how many customers they enrolled. Our RCT was layered on top of this contest and it tests the impact of three distinct behavioral framings: reminders that focus on agents' self-motivation by telling them how they can be the best agents; reminders that focus on agents' prosociality by emphasizing how the pension product can help families when they reach old age; and reminders that emphasize that the bank is monitoring agent performance. We also test the impact of varying the frequencies of these SMS reminders: over the contest' 4-week period, agents receive reminders once a week or three times a week.

We use the results from the first RCT to design two additional RCTs with agents associated with two different banks: Bank 1, known for its supportive culture, and Bank 2, known for the absence

[1] According to the most recent Findex survey, 69% of all adults globally own a bank account, half of them report saving in the past 12 months, and the percentage of adults with a mobile bank account in Africa has doubled since 2011 to a total of 21% (Demirguc-Kunt et al. 2018).

[2] Section 2.2 provides more details on APY, PMJJBY, PMSBY and their various features.

of this culture. For the subsequent two RCTs, we test the impact of sending SMS reminders three times a week for a period of three weeks. During the first and third weeks, reminders emphasize on self-motivation. During the second week, reminders focus on the agent network company and the bank closely monitoring performance. We send the SMS reminders during a period in which Bank 1 was conducting a contest to incentivize agents to increase enrollments in the Government's pension products.

In the presence of material incentives for performance like a contest, we expect that SMS messages are likely to remind agents that they are part of a contest, leading to a higher effort on their part to enroll customers in the APY program. SMS reminders can bring the details of the contest to "top of mind" (Karlan et al. 2016) by directing agents' attention to the importance of encouraging adoption of the pension product. We selected the behavioral framings of the reminders based on three possibilities: First, given that reminders are sent during a contest, agents could become more attentive to messaging that explicitly highlights competition (i.e. "be the best"). Second, agents might be encouraged to increase pension enrollments if their attention is directed towards the prosocial aspects of the product.[3] Finally, in line with the literature on audits and monitoring in works like Finan, Olken, and Pande (2017), agents might pay more attention to messages (and feel compelled to increase enrollments) if they are reminded that the bank is following their permanence closely.

Further, since agents may have limited cognitive resources like attention (Mullainathan and Shafir 2014), we expect that message frequency may affect agent performance. It is possible that messages sent multiple times a week make the reminders more salient for agents and make the behavioral framing more likely to be remembered. Furthermore, message frequency may matter differently for the various types of behavioral framings. In particular, sending multiple reminders per week might amplify or dampen the impact of specific behavioral framings. For example, reminders about monitoring sent with a higher frequency could enhance the perception that the bank is really monitoring performance, or could make the agents upset with the lack of trust on the part of the company and the bank. Finally, it is possible for the reminders to have a differential impact on the agents depending on whether they are sent at the beginning, the middle, or the end of the contest. Reminders close to the end of the contest could plausibly exhort agents to put in an extra amount of effort to be the "best" (i.e. personal motivation) given the short period of time left. Likewise, reminders sent at the beginning of the month could be effective at focusing agents'attention on the contest when they have few competing demands on their time, but their effect could dissipate later in the month.

For the first RCT in the short term, we find no statistically significant effect overall for any particular framing or frequency. However, we find that the effect of sending SMS reminders that focus on monitoring three times a week is positive and statistically significant. This treatment increases APY enrollment by 13.5% (or an average of 0.992 additional enrollments per agent). We also find suggestive evidence that SMS reminders have a differential impact depending on when they are sent during the contest. Three-times-a-week reminders that emphasize personal motivation are effective only during the first week, while three-times-a-week reminders warning agents that they are being monitored are effective towards the end of the contest. In the medium term, two months after the contest is conducted, we find statistically significant effects for sending SMS reminders three times a week, and also for the behavioral framing focused on monitoring.

For the second set of RCTs, we find that SMS reminders increase enrollments in the insurance

[3] McLeish and Oxoby (2011), among others, show that priming social identities matters for economic decision-making. In this context, agents could see themselves as important players in ensuring that their communities thrive. Or because of their identity as agents, they might really care about the perceptions of their peer group, similar to how bureaucrats in Nigeria improve performance based on social recognition in Gauri et al. (2018).

products for agents associated Bank 1 and who operate in a supportive environment. However, we find no effect on insurance enrollments when SMS reminders are sent to banking agents who are not associated with the less supportive Bank 2. Qualitative work conducted around the time that Bank 1 conducted its contest suggests that some agents might enroll customers in the insurance products without the customers' explicit permission, and that customers might not unenroll because of hassle factors. Taken together, the results provide evidence that SMS reminders to sent to banking agents can increase enrollments in pension and insurance products at the margin, but that incentives and reminders could potentially encourage agents to engage in suboptimal behavior.

This paper contributes to three key literatures. First, the results we present speak to the growing work that studies the impact of banking agents (and the mobile transactions they enable) on financial inclusion (Balasubramanian and Drake 2015; Suri 2017; Acimovic et al. 2019; De Gasperin, Rotondi, and Stanca 2019). By showing which types of SMS reminders work on agents and when, we also contribute to the literature investigating the use of "nudges" to further public policy goals in general and financial inclusion goals in particular (For instance: Thaler and Benartzi 2004; Ashraf, Karlan, and Yin 2006; Thaler and Sunstein 2009; Beshears et al. 2009; Bryan, Karlan, and Nelson 2010; Datta and Mullainathan 2014; Drexler, Fischer, and Schoar 2014). The majority of papers that use low-touch, behaviorally-informed interventions in financial inclusion have so far focused on changing relatively simple behaviors.[4] But we take the literature forward by testing whether SMS reminders can change more complex behaviors, namely encouraging the adoption of complicated financial products like pension and insurance by focusing on the agents and not the customers.

Finally, we contribute to the increasing number of studies that aim to understand how to motivate frontline workers in developing countries to provide better services. Recent work has focused on the incentives faced by individuals who act on behalf of the state (Finan, Olken, and Pande 2017); and on how intrinsic and extrinsic motivation can lead these individuals to improve the delivery of social services (Banerjee, Duflo, and Glennerster 2008; Duflo, Hanna, and Ryan 2012; Bertrand et al. 2016; Gauri et al. 2018; Ashraf, Bandiera, and Lee 2018; Duflo et al. 2018)[5][6]. The results in this paper suggest that behaviorally-informed SMS reminders sent at high frequencies emphasizing monitoring can amplify the effect of a supportive, involved work culture on the motivation of frontline workers as proxied by incentives like prizes for performance. These results are in line with recent work in Perú, which finds that sending SMS reminders to bureaucrats in a school maintenance program focused on monitoring increases compliance with program policies (Dustan et al. 2018).

The rest of the paper proceeds as follows. Section 2 provides some relevant background and

[4]Karlan et al. (2016) present evidence from three different countries suggesting that sending SMS reminders with specific savings goals and financial incentives lead to increased savings in bank accounts; Aker et al. (2018) find that, while a lockbox as a savings device allow households to mitigate negative health shocks, SMS reminders do not have an impact on financial behavior; Akbas et al. (2016) show that SMS reminders increase savings; Choi et al. (2017) show that changes in e-mail communication also increase savings; Karlan, Morten, and Zinman (2012) use SMS reminders to increase loan repayments. Other interventions using SMS reminders have tried to understand their impact on loan repayment in Uganda (Cadena and Schoar 2011), improving credit scores in the US (Bracha and Meier 2014), and creating savings habits among the youth in Colombia (Rodrıguez and Saavedra 2015) and among poorer people in Paraguay (Azevedo et al. 2019).

[5]While banking agents are not strictly speaking government employees, in the financial inclusion space they do closely resemble government frontline workers from other sectors. They tend to be associated with public sector banks and are often local shopkeepers from the same communities as their customers.

[6]The intersection between banking agents and the explicit provision of government services clearly comes out in the case of the e-mitras in the Indian state of Rajasthan. E-mitras are banking agents who, in addition to basic banking, also provide state services like utility bill payments and application for and digitally signatures of certificates. More information about the e-mitras can be found at http://emitra.rajasthan.gov.in/ .

presents the details of the products and the contests. Section 3 describes the data we use and shows some summary statistics for the agents covered by this study. Section 4 contains the main specifications used and discusses key econometric choices made for the analysis. Section 5 presents the main results. Finally, Section 6 concludes.

2. Background

2.1 Policy Environment

Banking agents, or simply agents, are an attractive proposition for banks. By leveraging local entrepreneurs, banks do not have to bear the full fixed cost of setting up bank branches and ATMs in underdeveloped markets. The Government of India created the legal framework for a banking agent model in 2006. That year, the Reserve Bank of India (RBI), India's central bank, released guidelines to allow banks to extend their services through third-party intermediaries, like agent network companies.[7] Banking agents offer customers selected services such as account opening, deposits, and withdrawals through the agents' retail points. They are associated with the branch of a specific bank as per the terms agreed upon with the agent network company, but they are not bank employees. Agents are hired, trained, and managed by the agent network companies.

The services banking agents provide include some of the Government of India flagship financial inclusion programs. Among the products offered are the Pradhan Mantri Jan Dhan Yojana (PMJDY), Pradhan Mantri Jeevan Jyoti Bima Yojana (PMJJBY), Pradhan Mantri Suraksha Bima Yojana (PMSBY) and Atal Pension Yojana (APY). PMJDY is a zero-balance account that includes accident insurance and an overdraft facility. PMJJBY is a life insurance product that provides a pay out of up to INR 200,000 (~ USD 2,800) to families in case of death of the policy holder. PMSBY is an accident insurance product that provides coverage of up to INR 100,000 (~ USD 1,400) in case of disability. Finally, APY is a pension product primarily focused on the unorganized sector. Anyone between the ages of 18 and 40 can enroll, with monthly premiums that vary according to age and eventual payouts ranging from INR 1,000 to 5,000 (USD 14 - 70).

2.2 APY Product Details

The APY program was officially launched by the Government of India in 2015. APY aims to be self-financing and is targeted toward the unorganized sector in India, which comprised 392 million people in 2011 (Srija, Shirke, and others 2014). So far, uptake of APY has been low. Official data reveals that only 2.4 million adults have enrolled, compared to the 32 million enrollments in the National Social Assistance Programme, a non-contributory social protection system that targets people with disabilities, widows, and the elderly (Drèze and Khera 2017). Part of the reason for the low enrollment in APY is possibly because the program details are complicated. The monthly contribution to the program varies with the age of the customer at the moment of enrollment, an annuity-based payout structure that can be difficult to understand. Customers also need to be enrolled in the program for 20 years to be able to receive a pension.[8] Understanding all the details of APY might make it difficult for low-income customers to enroll, and agents might not have incentives to provide additional help.

[7] The circular that RBI released enabling banks to outsource banking services through agents can be found in RBI archives: https://www.rbi.org.in/Scripts/NotificationUser.aspx?Id=2718&Mode=0

[8] The full details of APY as communicated by the Government of India can be found at https://npscra.nsdl.co.in/nsdl/scheme-details/APY_Scheme_Details.pdf

2.3 PMJJBY and PMSY Product Details

PMJJBY was launched in 2015 by the Government of India as a life insurance product with a yearly premium of INR 330 autodebited from the customer's bank account. The product provides the INR 200,000 pay-out to family members of the customer in case of death for any reason. Anyone between the ages of 18 - 50 is eligible to purchase this product, and it is provided by banks and major insurance companies like the Life Insurance Corporation. Also launched in 2015, PMSBY is an accident insurance that covers customers between the ages of 18 and 70. The yearly premium for PMSBY is INR 12, an amount that is autodebited from the customers' accounts every year. As of 2019, there are about 60 million customers enrolled in PMJJBY and 160 million enrolled in PMSBY.[9]

2.4 Contest by the Agent Network Company

For this study, we worked with an agent network company that covers more than 500 districts and with more than 21,000 agent points in India. During June 2019, the agent network ran a contest with 3,120 agents affiliated with a public sector bank (Bank 1). The aim was to incentivize them to enroll more customers in APY during that month. The contest awarded agents different prizes, such as laptop bags and wireless speakers, depending on the number of new APY enrollments. The agent network company communicated the details of the contest at the beginning of the month through a message on Whatsapp, a popular messaging application widely used in India. In addition, the agent network company also provided agents with a very simple explanation of the main features of the APY product through a Whatsapp info-graphic.

The contest was initially scheduled to run for three weeks. However, on the third week, the agent network company decided to extend the contest for an extra week. Information about the new deadline was also disseminated through Whatsapp and through on-the-ground sales executives. Given that APY is a complicated product and that there is some paperwork involved in enrolling new customers, we analyze the impact of the intervention one week after the contest concludes.This additional week provides a buffer for data coming in from agents who might have been successfully nudged on week four, but whose efforts did not materialize until week five.

2.5 Contest by the Public Sector Bank

From 15 August to 15 September 2019, a public sector bank conducted a contest in cooperation with the agent network company in order to increase PMJJBY and PMSBY enrollments. This was the same public sector bank with which agents in the June 2019 are associated (Bank 1). The top nine agents in the area with a minimum enrollment of 2,500 customers were awarded INR 7,000 and the top six agents nation-wide were congratulated publicly by the bank. Bank 1 is known for being more supportive and more engaged in financial inclusion as compared to similar public sector banks.

3. Data

Baseline data consisted of administrative records about the agents' demographic characteristics and agents' performance during May 2019 and August 2019 for the first RCT and the subsequent two RCTs, respectively. These are the pre-intervention months. We use the following demographic

[9]The Government of India is likely to increase the pay outs from these two programs and also increase the insurance premiums. More about these possible changes can be found at: https://www.thehindubusinessline.com/economy/centre-may-revamp-flagship-insurance-schemes/article29755580.ece

characteristics: gender, age, district, and employment period. To capture the previous month's performance, we use the number of APY enrollments, the number of PMJJBY enrollments and PMSBY enrollments, number of transactions, and enrollments in fixed/recurring deposits. For the RCT involving APY, we create a dummy to indicate whether agents had zero APY enrollments in the pre-intervention month. For the RCT on PMJJBY/PMSBY, we create a dummy to indicate zero PMSBY enrollments in the pre-intervention month.

For certain variables that contain a high proportion of zeroes, we use the inverse hyperbolic sine transformation (henceforth IHS), following Bellemare and Wichman (2019). The variables we transform are the number of APY, PMJJBY, and PMSBY enrollments in the previous month, and the total number of transactions. The outcome variable of primary interest are the number of new APY, PMJJBY, and PMSBY enrollments, all presented in IHS. For the randomization in the APY SMS intervention, we stratify based on whether the number of APY enrollments in the pre-intervention month was zero and on the quartile of number of total customer transactions. We follow a similar stratification procedure for the PMJJBY/PMSBY intervention, stratifying on whether the number of PMSBY enrollments in the pre-intervention is zero and on the quartile of total transactions. Where baseline values for the variable age are missing on the APY intervention, we impute the average age in the dataset. For missing values in the variable that captures time spent at the agent network and gender, we impute the modal value. We change this procedure for missing values in the subsequent two RCTs, where we input zero for missing values in the variables age and time at the agent network, and create dummies that indicate whether the values are missing.

Table 1 presents the main characteristics of the sample for Bank 1. The sample includes 3,120 agents affiliated with Bank 1 in India all across the country. Agents in the sample are on average 33 years old, are almost exclusively male (only 7% of all the sample is female), and have spent on average 3 years working for the agent network (1,096 days). Table 2 presents the main characteristics for the 3,398 banking agents affiliated with Bank 1 in August 2019 who participated in the SMS reminder intervention in September. Table 3 presents similar characteristics for the 1,781 banking agents affiliated with Bank 2.

Figure 2 shows the distribution of APY enrollments in the pre-intervention month for Bank 1. As figure 2 shows, the number of monthly enrollments is very low and the distribution is heavily skewed. In fact, 72.6% of all agents in the sample did not enroll any customer in the APY product during this month. The average number of APY enrollments per agent in the pre-intervention month is 1.4, with a maximum of 213 enrollments.

Figures 3 and 4 show the distribution of PMJJBY and PMSBY accounts for the pre-intervention month. For Bank 1, 83.9% of agents had zero enrollments in PMJJBY and 61.7% in PMSBY. For Bank 2, 71% of agents had zero enrollments in PMJJBY and 42.8% in PMSBY.

4. Empirical Strategy

This section explains our main strategy to estimate the impact of the different behavioral framings and frequencies on pension and insurance enrollments. Figure 1 provides a high-level overview of the timeline for the three RCTs we implement.

4.1 APY Contest

During a month-long contest to increase enrollments in a pension product (APY), we estimate the effect of sending behaviorally-informed SMS reminders to banking agents. As mentioned in the previous sections, the agent network company awarded agents different prizes depending on the number of new APY enrollments during the month of June, 2019. We test the impact of sending SMS reminders once a week and thrice a week, as well as the impact of three different behavioral framings: personal motivation, prosociality, and monitoring. We measure the outcome variable in the short term, June 2019 and but also in the medium term two months later, August 2019.

We implemented a cross-cutting design similar to the ones described in Duflo, Glennerster, and Kremer (2007). We randomly assigned agents to six treatment groups and one control group, stratifying on whether APY enrollments were zero or not during the pre-intervention month and on the quartile of agent transactions. From the 3,120, 18% were assigned to be part of the control group (a total of 558). Each treatment group was defined at the frequency-framing level. This means that each treatment group received one of the three behaviorally-informed framings (personal motivation, prosociality, monitoring) in one of the two frequencies (once a week, thrice a week). Table 4 presents the seven randomized groups as well as the number of agents per group.

To estimate the impact of the interaction between frequency and behaviorally-informed SMS reminder, we use the following equation:

$$Y_{ist} = \beta_1 PO_{is} + \beta_2 SO_{is} + \beta_3 MO_{is} + \beta_4 PT_{is} + \beta_5 ST_{is} + \beta_6 MT_{is} + Y_{ist-1} + \lambda_s + D_i + X'_{is}\delta + \epsilon_{is} \tag{1}$$

In equation (1), Y_{ist} denotes the total number of new APY enrollments at the end of the intervention month (short-term) and then two months later (medium-term) for agent i in strata s at time t;Y_{ist-1} denotes the total number of new APY enrollments during the pre-intervention month; PO_{is} is a dummy on whether the agent received the personal motivation reminder once a week; SO_{is} indicates whether the agent received the prosociality reminder once a week; MO_{is} indicates whether the agent received the monitoring reminder once a week. Similarly, the dummies PT_{is}, ST_{is}, and MT_{is} indicate whether the agent received the personal motivation, prosociality, and monitoring reminders three times a week. The coefficient β_1 is interpreted as the average marginal increase in APY enrollments when agents receive the personal motivation reminder once a week when the variable has not been transformed with the inverse hyperbolic sine (IHS) transformation. When the outcome variable Y_{ist} is in IHS, we follow the approximation in Bellemare and Wichman (2019) and interpret $e^{\beta_1} - 1$ as the approximate percentage change in APY enrollments when the agents belong to that particular treatment. β_2 to β_6 have similar interpretations for the interactions between behavioral framing and frequency.

λ_s strata fixed effects. D_i captures the district fixed effects. X_{is} is a vector of baseline-level controls for agent i in strata s (APY, PMJJDY, and PMSBY enrollments in the pre-intervention month; pre-intervention number of transactions; gender, age, and employment period).

We include PMJJY and PMSBY enrollments because of their potential correlation with APY. PMJJBY, PMSBY, and APY are the three products that constitute the low cost, pro-poor social protection schemes that the Government of India promotes for financial inclusion. Therefore, enrollment in one of these schemes plausibly captures unobservables related to customer enrollments in APY. Finally, ϵ_{is} captures the error term. All reported standard errors are heteroskedasticity-robust. The specification in equation (1) reflects the level at which the treatment groups where randomized, and therefore addresses some of the issues raised in Muralidharan, Romero, and Wüthrich (2019).

To make sure that the randomization achieved balance between the treatment and control groups, we test for joint orthogonality using the following specification[10]:

[10] The idea for this joint test of orthogonality is discussed on a blog post on the World Bank's Development Impact blog: https://blogs.worldbank.org/impactevaluations/tools-trade-joint-test-orthogonality-when-testing-balance

$$T_{is} = \alpha + X'_{is}\delta + \lambda_s + \epsilon_{is} \tag{2}$$

In equation (2), T_{is} is a dummy variable that denotes whether agent i in strata s belongs to one of the six treatment groups. X_{is} denotes the baseline characteristics for agent i used as controls in the analysis as in equation (1). λ_s captures the strata fixed effects. Finally, ϵ_{is} captures the error term. We then look at the F-test for each regression equation, and find that the p-value for the entire model is substantially greater than 0.05. This means that the model that uses our covariates to explain treatment assignment is not a good fit. Tables 14 and 15 in the appendix present the relevant regressions.

We also estimate the impact of the interaction between frequency and behavioral framing by week with the following specification:

$$Y_{ist} = \beta_1 PO_{is} + \beta_2 SO_{is} + \beta_3 MO_{is} + \beta_4 PT_{is} + \beta_5 ST_{is} + \beta_6 MT_{is} + Y_{ist-1} + \lambda_s + D_i + X'_{is}\delta + \epsilon_{is} \tag{3}$$

The key differences between equation (1) and equation (3) are on the meaning of Y_{ist}. In equation (3), Y_{ist} captures total APY enrollments *on a specific week.* This means that we use this equation to estimate the impact of the different framing-frequency interactions for each of the five weeks individually. In this way, we can estimate the impact of the SMS reminders and their frequency on weekly APY enrollments. We only estimate the weekly impact of the different SMS reminders in for the intervention month.

To obtain the impact of sending the SMS reminders either once a week or three times a week, conditional on the reminders having a specific behavioral frame, we use the following specification:

$$Y_{ist} = \beta_1 ONCE_{is} + \beta_2 THRICE_{is} + Y_{ist-1} + \lambda_s + D_i + X'_{is}\delta + \epsilon_{is} \tag{4}$$

All the parameters in equation (4) are the same as equation (1), except for the variables $ONCE_{is}$ and $THRICE_{is}$. These dummies denote whether agent i in strata s received reminders either once or three times a week. We use this specification both for the intervention month (short-term) and two months later (medium-term).

We estimate the impact of each behavioral framing conditional on an agent receiving an SMS reminder either once or three times a week using the following specification:

$$Y_{ist} = \beta_1 PER_{is} + \beta_2 PRO_{is} + \beta_3 MONI_{is} + Y_{ist-1} + \lambda_s + D_i + X'_{is}\delta + \epsilon_{is} \tag{5}$$

Again, equation (5) contains the same controls and fixed-effects as equations (1) and (4). The only difference is that in this specification, PER_{is} is a dummy that captures whether agent i in strata s received SMS reminders that focused on personal motivation; PRO_{is} if the reminders focused on personal motivation and $MONI_{is}$ if they focused on monitoring. We use the same specification to estimate the impact of the behavioral framings on enrollments both for the short-term and the medium term.

All of these specifications estimate the intent-to-treat (ITT) effect and do not take into account whether agents actually received the SMS reminder/phone call or not. Close to 88% of all SMS reminders where delivered, with the number being consistent across treatment groups and the control.

4.2 PMJJBY/PMSBY Contest

Based on the results from our first RCT, we designed an RCT to estimate the effects of sending behaviorally-informed messages on enrollments in two additional product categories: PMJJBY and PMSBY. For the randomization, we stratify on whether or not the pre-intervention number of PMSBY enrollment was zero and on the quartile of transactions.

We conducted the additional RCTs on two distinct samples. The first sample includes 3,398 banking agents affiliated to a large public sector bank, the same bank whose agents participated in the contest run by the agent network (Bank 1). Bank 1 is generally known in the sector for being more supportive and directly involved in financial inclusion. Most of the agents in this sample were in fact included in the sample for the first RCT. The second sample is composed of 1,781 agents affiliated with a different public sector bank, Bank 2. Bank 1 conducted a contest for a month starting on August 15 and ending on September 15. During this contest, Bank 1 offered to publicly congratulate the agents that enrolled the highest number of new customers on PMJJBY and PMSBY, and included a monetary reward of INR 7,000 for the top nine agents. Bank 2 did not conduct any contest.

We sent SMS reminders to both sets of agents for three weeks starting on the first week of September. SMS reminders on week one were about personal motivation, emphasizing that the agents could be the best by enrolling more customers. Reminders on week two highlighted that the bank was closely monitoring agent performance. These messages were timed to coincide with the final week of the contest for Bank 1. Finally, messages on week three focused once again on personal motivation. SMS reminders sent to agents affiliated with bank one also made a reference to the contest. Besides that reference, reminders sent to both sets of agents were identical.

We use the following equation to estimate the impact of sending these SMS reminders on total combined enrollment in PMJJBY and PMSBY:

$$Y_{ist} = \beta_1 SMS_{is} + Y_{ist-1} + \lambda_s + D_i + X'_{is}\delta + \epsilon_{is} \tag{6}$$

Outcome variable Y_{ist} in equation (6) is the total number of new enrollments in PMJJBY and PMSBY at the end of September. SMS_{is} is a dummy that indicates whether agent i was included in the treatment; Y_{ist-1} is the number of total PMJJBY and PMSBY enrollments in August; λ_s are strata fixed effects. All the other variables have the same interpretation as the ones in equation (1). We use this specification for agents affiliated with both Bank 1 and Bank 2.

5. Results

In this section, we present the results using the empirical strategy laid out in Section 4. We begin with the results for SMS reminders sent during the APY contest and then discuss the results of the reminders sent in the context of PMJJBY and PMSBY. For the APY contest, we first present the main results during the intervention month, namely, the estimates of the interactions between the three different types of behavioral framings (personal motivation, prosociality, and monitoring) and the frequency (once a week and three times a week) as described in equation (1). These are the main results since this is the level at which agents were randomly assigned to different treatment and control groups. We proceed to show that, in line with theoretical expectations, behavioral framings have differential impacts on APY enrollment depending on how far along the contest they were sent. We then present the impact of the three behavioral framings and the frequencies separately on APY enrollments during the intervention month. We carry out a similar analysis for the medium term, or two months after the intervention, where we analyze the impact of the interactions, and the framings and frequencies separately. We end by presenting the results of the second and third RCTs, sending SMS reminders to agents associated with Bank 1 and Bank 2 on total PMJJBY and PMBYS enrollments.

5.1 APY Main Results: Interactions

Table 5 presents the main results of the SMS reminders on total APY enrollments during the intervention month as estimated using equation (1). Our preferred specification is the one that uses the IHS transformation for certain control variables and for the main outcome variable. This is specification 2 in table 5. We show the specifications where the outcome variable is not IHS transformed as a robustness check. The average enrollment per agent in the control group at the end of 5 weeks is 1.78. For the treatment group who received SMS reminders three times a week emphasizing monitoring, we estimate an average increase of 13.4%[11] or 0.24 additional enrollments per agent. We also find that it costs approximately INR 7.5 to generate an additional customer enrollment in APY for this treatment. To measure cost-effectiveness, we carry out the following calculation:

$$\frac{ReminderCost * TimesWeek * NumWeeks * NumAgents}{Effect * NumAgents} \tag{7}$$

In which $ReminderCost = 0.15$, $TimesWeek = 3$, $NumWeeks = 4$, $NumAgents = 432$, and $Effect = 0.24$. None of the other treatment arms led to a statistically significant change in APY enrollments.

Table 6 presents the effect of the SMS reminders on total APY enrollments in August, two months after the initial contest ended. We estimate that receiving an SMS three times a week with messaging around monitoring leads to an increase of 17.7%[12] in APY enrollments compared to a control mean of 2.05 enrollments. Personal motivation reminders sent three times a week lead to an estimated 15.8%[13] increase in APY enrollments. While the coefficient on sending SMS reminders around monitoring once a week is significant in our main specification, it does not survive the FDR multiple hypothesis correction. Given that the corrected p-value is 0.06, we interpret this as weak evidence of an effect. It is possible that the monitoring reminders are especially salient to agents because of the contest carried out two months before. Additionally, the agent network company temporarily suspended some agents' ability to carry out transactions other than pension enrollments. Thus, the SMS reminders might have become a credible threat that encourage agents to increase enrollments even two months after the reminders were sent.

5.2 APY Interactions by Week, Intervention Month

Table 7 presents the effects of the interactions disaggregated by week for the intervention month, using the estimation equation (3). On week four, the monitoring SMS reminders sent three times a week have a positive, statistically significant effect. The effect of these reminders on week three do not survive the FDR correction for multiple hypothesis testing, but the small adjusted p-value of 0.061 presents weak evidence that this treatment might have had an effect. These results are also presented in Figure 5. Table 16 in the appendix presents the same results with an outcome variable without the IHS transformation for robustness. The results suggest that agents become

[11] We use the result that the percentage change in enrollments can be approximated by $e^{\beta_1} - 1$ as suggested in Bellemare and Wichman (2019)

[12] $e^{0.163} - 1 = 0.177$

[13] $e^{0.147} - 1 = 0.158$

sensitive to the monitoring SMS reminders when they are approaching the deadline of the contest. As explained in the previous section, during week three of the contest the agent network suddenly extended the deadline by a week. This means that agents faced two deadlines: the one stated at the onset of the contest at the end of week three, and the sudden new deadline at the end of week four. One possibility is that because of the deadlines, the SMS reminders sent three times a week around monitoring made the contest more salient, increasing agents' attention to the contest and thereby making a marginal additional effort to enroll customers.

5.3 APY Frequency and Behavioral Framings

Table 8 shows the impact of the SMS reminder frequency during the intervention month and table 8 shows the results two months later as estimated using equation (5). Tables 10 and 11 show the impact of the three different behavioral framings for the intervention month and two months later, respectively. We find no statistically significant effect of either one frequencies alone during the intervention month. However, sending these SMS reminders three times a week leads to a 14.1%[14] increase in APY enrollments two months after the contest is over. In terms of framings, we also find no impact of SMS reminders appealing to any of the behavioral framings during the intervention month, though the effect of SMS reminders that focus on bank monitoring is significant at the 10% level and the FDR-adjusted p-value is 0.031. We do find that the monitoring SMS reminders lead to an increase of 16.3%[15] increase in APY enrollments two months later.

These results present at least two distinct possibilities. First, weak evidence on the effect of the three times a week frequency from the main specification (unadjusted p-value of 0.104 and FDR-adjusted p-value of 0.052), alternative specifications, and the effect two months later suggests that the effect of sending SMS reminders could be cumulative simply because agents are constantly reminded to perform a specific activity. Second, it is also possible that the agent feels more supported by the agent network is there is more SMS communication. In the medium term, it is likely that the agents who received the monitoring reminders three times a week enrolled more customers because they see they there is a credible threat of the agent network temporarily suspending their accounts. This is also true for the effect of the monitoring framing.

5.4 PMJJBY/PMSBY Intervention

Tables 12 and 12 present the main results on total PMJJBY and PMSBY enrollment from sending SMS reminders to agents affiliated with Bank 1 and Bank 2 respectively. For both banks, we send SMS reminders three times a week for three weeks encouraging agents to enroll more customers both in PMJJBY and PMSBY: the first week, reminders focus on personal motivation; the second week, they focus on monitoring and are sent right before the deadline of the contest run by Bank 1; and on week three, they again focus on personal motivation. In addition, reminders sent to Bank 1 mention the contest that Bank 1 is conducting.

For agents affiliated with Bank 1, we estimate that sending these SMS reminders lead to an average increase of 10.4%[16] total enrollments on both insurance products over a control mean of 6.68. Using the same formula as in section 5.1, we estimate that it costs INR 1.94 on average to generate one additional enrollment in the insurance products. Tables 17 and 18 in the appendix show that these effects are primarily driven by additional enrollments in PMSBY. The estimated effects of the SMS reminders on combined PMJJBY and PMSBY enrollments as well as on each

[14] $e^{0.132} - 1 = 0.141$
[15] $e^{0.151} - 1 = 0.163$
[16] $e^{0.099} - 1 = 0.104$

product category separately are robust to multiple hypothesis FDR corrections. As table 13 shows, we find no statistically significant effect on sending behaviorally-informed reminders to agents affiliated with Bank 2 on PMJJBY and PMSBY enrollments. Tables 19 and 20 in the appendix break down this result by product category.

While we can't compare Bank 1 to Bank 2 directly, one possible reason why the SMS reminders worked with Bank 1 agents is the contest. Bank 1 promised a monetary compensation and social recognition to the top performing agents during the contest it conducted. The SMS reminders plausibly were effective at the margins because they reminded agents of the potential material and social rewards from enrolling more costumers. Behaviorally-informed SMS reminders might therefore work best when there are other social and material incentives at play. However, we are unable to provide any evidence for this hypothesis given our setup. A future experiment could potentially allocate one group of agents randomly to being part of a contest and another one to "business as usual" in order to disentangle the effects of the contest itself. A behaviorally-informed intervention could then be layered on top to find the causal impact of the reminders for agents both in the contest and the business-as-usual conditions.

Given that the monitoring SMS reminders were effective at increasing enrollments in APY, the pension product, and in combination with personal motivation messaging, were also effective at increasing enrollments in the PMJJBY and PMSBY insurance products, a caveat is in place. There are at least two mechanisms by which these behaviorally-informed reminders could have increased enrollments. SMS reminders could encourage agents to provide a more client-centric service, disseminating more accurate information about these government programs or providing customers with extra support to enroll. It is also possible, however, that agents increase enrollments by signing customers up for these programs without customers' consent or full information. Some of the qualitative work that we conducted around the SMS reminders does suggest that enrolling customers in these programs without their consent is possible and indeed is happening in some cases. Nevertheless, our evidence on this point is purely anecdotal. Future work can consider ways to disentangle the mechanisms by which agents actually increase enrollments, given that some agent behavior might not be in the best interest of the customers.

6. Conclusion

We experimentally evaluate the marginal impact of sending behaviorally-informed SMS reminders to banking agents on customers enrollment in a government pension product and two insurance products, the Atal Pension Yojana (APY), the Pradhan Mantri Jeevan Jyoti Bima Yojana (PMJJBY) and the Pradhan Mantri Suraksha Bima Yojana (PMSBY). For the enrollments in the pension product, we vary the type of behavioral framing used as well as the SMS reminder frequency. The experimental design is layered on top of a month-long contest in June, 2019 in which an agent network company incentivized agents to increase enrollment through performance-based prizes. We then take the main results from the first experiment and test whether the behavioral framings and frequency that "worked" in the first experiment are effective at increasing enrollments in PMJJBY and PMSBY. We conduct two experiments: one with a sample of agents associated with the same bank as in the APY experiment, Bank 1, and one with a sample of agents who belong to a different public bank, Bank2.

We find a positive and statistically significant effect on APY enrollments of sending SMS reminders three times a week emphasizing monitoring when the agent network conducts a contest based on agent performance. This treatment leads to an increase in enrollments that persists two months after the reminders are initially sent. The analysis from section 5.2 suggests that this is primarily driven by making the deadline of the contest salient. SMS reminders are cost-effective for the treatment arm that drives a big part of the results presented in the study (monitoring, three times a week as presented in Table 4). Taking only the variable costs of the actual SMS reminders into account, on average it costs INR 7.5 to generate an additional customer enrollment in the pension product. There is no statistically significant effect of any of the behavioral framings or frequencies alone. However, we find that two months after the contest is over, there is a positive and statistically significant effect of the three-times-a-week and the monitoring treatments. We also find that reminders that emphasize personal motivation and monitoring sent at high frequencies increase enrollments in two government insurance products, PMJJBY and PMSBY, but only for agents associated with a bank known for being more involved and supportive of financial inclusion activities.

For the first RCT, there are several possibilities for why the three behavioral framings in isolation might have not had an effect. First of all, selling a pension product is hard. The actuarial details of the product might be difficult to explain, the product requires customers to make regular contributions, and the benefits only materialize in the distant future. In this context, simple reminders that appeal to personal motivation or agent monitoring might not be enough for agents to increase product uptake. For the second and third RCTs, we interpret the results as suggesting that behaviorally-informed reminders are effective primarily when they are conducted in a supportive environment as proxied by prizes for performance. However, we are unable to rule out other reasons why SMS reminders did not lead to additional enrollments in Bank 2.

One of the merits of this study is that it was done at scale. Agents who were part of the study work in agent points all across the country and are likely representative of agents at other public sector banks more generally. This study was also conducted within a business setting, so it is easily scalable both internally for the agent network company and externally to similar organizations. Finally, a wide number of organizations in the financial inclusion space routinely use SMS to communicate with agents and customers alike. Estimating the impact of SMS reminders on uptake of different financial products is a first step in understanding how to communicate information in the financial inclusion space more generally.

A major limitation of the current study is the absence of additional data to understand the change in agents' behavior. The current analysis suggests that the three-times-a-week SMS reminders focused on monitoring were effective because they made the the material incentives that agents face salient. For instance, it is difficult to know if agents engaged in predatory practices that induced customers to take up a product they didn't need, or if they improved interactions with customers, thereby providing a better service. The qualitative work we conducted suggests that some agents do enroll customers into products without giving them full information, but we are unable to say how prevalent this practice might be. Additional qualitative work coupled with quantitative data could have provided a fuller picture of the mechanisms at work. This is an important area for future research that speaks to work like Finan, Olken, and Pande (2017). Ultimately, the aim of motivating and incentivizing frontline workers is to improve service delivery.

Future work could provide a more detailed picture behind the mechanisms that drive the impact of the monitory-frequency interaction. On the customer side, it might be possible to collect information about the customer's experience and satisfaction with the pension product. These data, combined with additional indicators for the accuracy of understanding the details of the pension and insurance products, can provide an indication of how much the additional uptake is driven by a genuine positive valuation of this type of programs. Other studies can also show whether the results from this paper hold true for other products. Finally, some of the interventions in this study were conducted while there were specific material incentives for the agents to increase pension and insurance enrollments. While we do implement an intervention with agents who do not face external incentives, our data does not allow us to make broad inferences. Future work can explore whether SMS reminders to agents only work when other incentives are at play, or whether their effect persists in the absence of an underlying external incentive for both pension and insurance.

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Tables

Table 1: Bank 1 Agent Characteristics, May 2019

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Time at Agent Network (Days)	3,120	1,159.45	679.91	0	514	1,753.2	2,484
Number of Transactions	3,120	552.24	689.34	0	94.8	768	6,124
APY Enrollments	3,120	1.41	5.85	0	0	1	213
Age	3,120	33.82	8.12	19	28	38	80
Gender (=1 if Female)	3,120	0.07	0.26	0	0	0	1
APY Enrollments (IHS)	3,120	0.50	0.94	0	0	0.9	6

Table 2: Bank 1 Agent Characteristics, Aug 2019

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Age	3,398	32.98	9.06	0.00	27.46	37.86	79.59
Time at Agent Network (Days)	3,398	1,064.59	724.89	0	420	1,717	2,484
PMSBY Enrollments	3,398	4.31	16.19	0	0	2	384
PMJJBY Enrollments	3,398	0.79	6.49	0	0	0	329
Gender (=1 if Female)	3,398	0.13	0.34	0	0	0	1
PMSBY Enrollments (IHS)	3,398	0.87	1.33	0	0	1.4	7
PMJJBY Enrollments (IHS)	3,398	0.26	0.71	0	0	0	6

Table 3: Bank 2 Agent Characteristics, Aug 2019

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Number of Transactions	1,781	584.36	716.53	0	82	856	7,171
PMSBY Enrollments	1,781	11.56	24.70	0	0	12	283
PMJJBY Enrollments	1,781	2.41	9.45	0	0	1	170
Missing 'Time at Network'	1,781	0.60	0.49	0	0	1	1
Gender (=1 if Female)	1,781	0.12	0.33	0	0	0	1
PMSBY Enrollments (IHS)	1,781	1.64	1.74	0	0	3.2	6
PMJJBY Enrollments (IHS)	1,781	0.58	1.10	0	0	0.9	6

Table 4: Cross-cutting Design for SMS Reminders Intervention

	Once a Week	Three Times a Week	Control
Personal Motivation	425	429	
Prosociality	426	425	
Monitoring	426	431	
Control			558

Table 5: Effect of Interactions, Bank 1 Intervention Month

	IHS of APY Enrollments		APY Enrollments	
	(1)	(2)	(3)	(4)
Personal Motivation, Once	0.025	−0.026	0.373	0.006
	(0.060)	(0.061)	(0.328)	(0.350)
Prosociality, Once	0.112*	0.046	0.443	0.025
	(0.061)	(0.060)	(0.286)	(0.332)
Monitoring, Once	0.060	0.059	0.269	0.196
	(0.060)	(0.060)	(0.291)	(0.327)
Personal Motivation, Three Times	0.119**	0.053	0.927*	0.592
	(0.060)	(0.060)	(0.498)	(0.486)
Prosociality, Three Times	0.036	0.027	0.103	0.186
	(0.060)	(0.060)	(0.269)	(0.296)
Monitoring, Three Times	0.135**	0.126**	1.047**	0.966**
	(0.064)	(0.064)	(0.419)	(0.435)
Strata fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
Avg APY Enrollments in Control Group	1.78			
FDR p-value, x3 Monitoring	0.025			
N	3,120	3,120	3,120	3,120
R^2	0.488	0.622	0.186	0.330
Adjusted R^2	0.486	0.575	0.183	0.247

Notes:

This table presents the results from estimating equation 1, where the outcome variable is total Atal Pension Yojana enrollments at the end of 5 weeks. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. The table also shows the adjusted p-value using the FDR correction for monitoring x3 a week. Note: *p<0.1;**p<0.05; ***p<0.01

Table 6: Effect of Interactions, Bank 1 Medium Term

	IHS of APY Enrollments		APY Enrollments	
	(1)	(2)	(3)	(4)
Personal Motivation, Once	−0.008	−0.035	−0.002	−0.314
	(0.058)	(0.059)	(0.292)	(0.291)
Prosociality, Once	0.106*	0.058	0.667*	0.502
	(0.061)	(0.062)	(0.399)	(0.410)
Monitoring, Once	0.096	0.139**	0.649	0.817**
	(0.062)	(0.064)	(0.415)	(0.417)
Personal Motivation, Three Times	0.137**	0.147**	0.909**	0.928**
	(0.062)	(0.064)	(0.404)	(0.415)
Prosociality, Three Times	0.057	0.083	0.344	0.441
	(0.060)	(0.062)	(0.362)	(0.394)
Monitoring, Three Times	0.123*	0.163**	0.757**	0.815**
	(0.064)	(0.065)	(0.345)	(0.366)
Strata fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
Avg APY Enrollments in Control Group	2.05			
FDR p-value, x1 Monitoring	0.06			
FDR p-value, x3 Personal Motivation	0.023			
FDR p-value, x3 Monitoring	0.012			
N	3,120	3,120	3,120	3,120
R^2	0.415	0.558	0.138	0.300
Adjusted R^2	0.413	0.503	0.135	0.214

Notes:

This table presents the results from estimating equation 1, where the outcome variable is total Atal Pension Yojana enrollments two months after the intervention. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. The table also shows the adjusted p-value using the FDR correction for monitoring x3 a week. Note: *p<0.1;**p<0.05; ***p<0.01

Table 7: Effect of Interactions by Week, Bank 1 Intervention Month

	IHS of Total APY Enrollments				
	Week 1	Week 2	Week 3	Week 4	Week 5
	(1)	(2)	(3)	(4)	(5)
Personal Motivation, Once	−0.013	−0.026	0.011	−0.012	−0.007
	(0.030)	(0.037)	(0.039)	(0.044)	(0.033)
Prosociality, Once	0.033	−0.002	0.040	0.023	−0.039
	(0.033)	(0.038)	(0.040)	(0.040)	(0.034)
Monitoring, Once	0.042	0.029	0.031	0.004	0.004
	(0.032)	(0.039)	(0.038)	(0.041)	(0.034)
Personal Motivation, Three Times	0.063*	−0.003	0.042	0.021	−0.007
	(0.034)	(0.038)	(0.040)	(0.042)	(0.035)
Prosociality, Three Times	0.011	0.019	0.033	0.026	−0.015
	(0.030)	(0.037)	(0.038)	(0.041)	(0.033)
Monitoring, Three Times	0.017	−0.001	0.090**	0.124***	0.036
	(0.032)	(0.038)	(0.043)	(0.046)	(0.036)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
FDR p-value, x3 Monitoring Week 3	0.069				
FDR p-value, x3 Monitoring Week 4	0.027				
N	3,120	3,120	3,120	3,120	3,120
R^2	0.326	0.410	0.364	0.378	0.340
Adjusted R^2	0.243	0.337	0.285	0.301	0.258

Notes:

This table presents the results from estimating equation 3, where the outcome variable is IHS-transformed total Atal Pension Yojana enrollments at the end of each of the 5 weeks. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. The table also shows the adjusted p-value using the FDR correction for monitoring x3 a week on weeks 3 and 4. Note: *p<0.1;**p<0.05; ***p<0.01

Table 8: Effect of Frequency, Bank 1 Intervention Month

	IHS of APY Enrollments		APY Enrollments	
	(1)	(2)	(3)	(4)
Once a Week	0.066	0.027	0.362	0.076
	(0.047)	(0.048)	(0.227)	(0.256)
Three Times a Week	0.097**	0.070	0.695**	0.585*
	(0.048)	(0.048)	(0.276)	(0.307)
Strata fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
FDR p-value, Three Times a Week	0.074			
N	3,120	3,120	3,120	3,120
R^2	0.487	0.621	0.185	0.329
Adjusted R^2	0.486	0.575	0.183	0.247

Notes:

This table presents the results from estimating equation 4, where the outcome variable is total Atal Pension Yojana enrollments at the end of 5 weeks. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 9: Effect of Frequency, Bank 1 Medium Term

	IHS of APY Enrollments		APY Enrollments	
	(1)	(2)	(3)	(4)
Once a Week	0.065	0.054	0.439*	0.336
	(0.047)	(0.050)	(0.263)	(0.274)
Three Times a Week	0.106**	0.132***	0.671**	0.736***
	(0.048)	(0.050)	(0.262)	(0.284)
Strata fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
FDR p-value, Three Times a Week	0.009			
N	3,120	3,120	3,120	3,120
R^2	0.414	0.557	0.137	0.298
Adjusted R^2	0.413	0.503	0.135	0.212

Notes:

This table presents the results from estimating equation 4, where the outcome variable is total Atal Pension Yojana enrollments at the end of August. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 10: Effect of Framing, Bank 1 Intervention Month

	IHS of APY Enrollments		APY Enrollments	
	(1)	(2)	(3)	(4)
Personal Motivation	0.072	0.013	0.651**	0.299
	(0.051)	(0.051)	(0.324)	(0.327)
Prosociality	0.074	0.037	0.273	0.102
	(0.051)	(0.051)	(0.233)	(0.267)
Monitoring	0.098*	0.093*	0.660**	0.584*
	(0.052)	(0.052)	(0.285)	(0.311)
Strata fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
FDR p-value, Monitoring	0.037			
N	3,120	3,120	3,120	3,120
R^2	0.487	0.621	0.185	0.328
Adjusted R^2	0.486	0.575	0.183	0.246

Notes:

This table presents the results from estimating equation 5, where the outcome variable is total Atal Pension Yojana enrollments at the end of 5 weeks. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 11: Effect of Framing, Bank 1 Medium Term

	IHS of APY Enrollments		APY Enrollments	
	(1)	(2)	(3)	(4)
Personal Motivation	0.065	0.056	0.456	0.308
	(0.050)	(0.053)	(0.282)	(0.290)
Prosociality	0.081	0.071	0.506*	0.477
	(0.051)	(0.053)	(0.299)	(0.335)
Monitoring	0.109**	0.151***	0.703**	0.812**
	(0.052)	(0.054)	(0.299)	(0.316)
Strata fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
FDR p-value, Monitoring	0.006			
N	3,120	3,120	3,120	3,120
R^2	0.414	0.557	0.137	0.298
Adjusted R^2	0.413	0.502	0.135	0.212

Notes:

This table presents the results from estimating equation 5, where the outcome variable is total Atal Pension Yojana enrollments at the end of August. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 12: Effect of SMS on Total PMJJBY/PMSBY Enrollments, Bank 1

	IHS of Total PMJJBY/PMSBY		Total PMJJBY/PMSBY	
	(1)	(2)	(3)	(4)
SMS	0.062	0.102**	1.349*	1.663**
	(0.044)	(0.042)	(0.705)	(0.692)
Stratification fixed effects	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
N	3,398	3,398	3,398	3,398
R^2	0.566	0.723	0.204	0.421
Adjusted R^2	0.566	0.685	0.203	0.341

Notes:

This table presents the results from estimating equation 7, where the outcome variable is total PMJJBY and PMSBY enrollments at the end of September Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 13: Effect of SMS on Total PMJJBY/PMSBY Enrollments, Bank 2

	IHS of Total PMJJBY/PMSBY		Total PMJJBY/PMSBY	
	(1)	(2)	(3)	(4)
SMS	0.0001	0.034	−0.404	−0.080
	(0.059)	(0.056)	(0.789)	(0.852)
Stratification fixed effects	Yes	Yes		
District fixed effects	No	Yes		
Controls	No	Yes		
N	1,781	1,781	1,781	1,781
R^2	0.375	0.635	0.157	0.462
Adjusted R^2	0.373	0.548	0.154	0.333

Notes:

This table presents the results from estimating equation 7, where the outcome variable is total PMJJBY and PMSBY enrollments at the end of September Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Figures

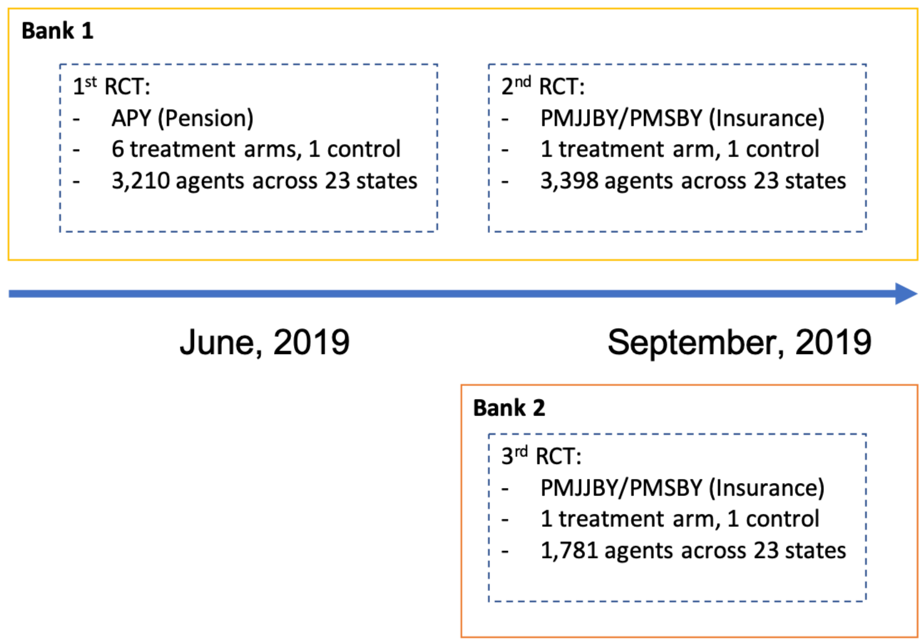

Figure 1: Overall Timeline

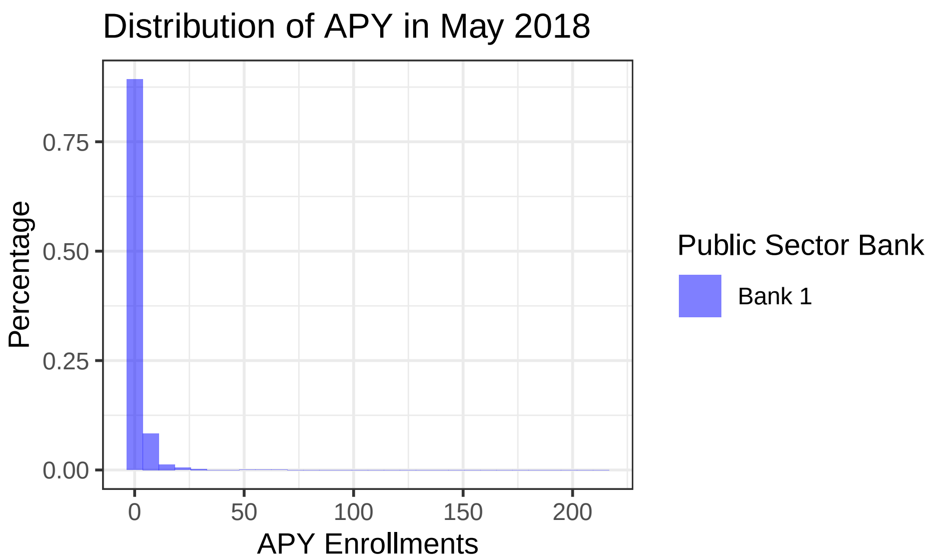

Figure 2: Distribution of APY Enrollments in the Month Before the Contest

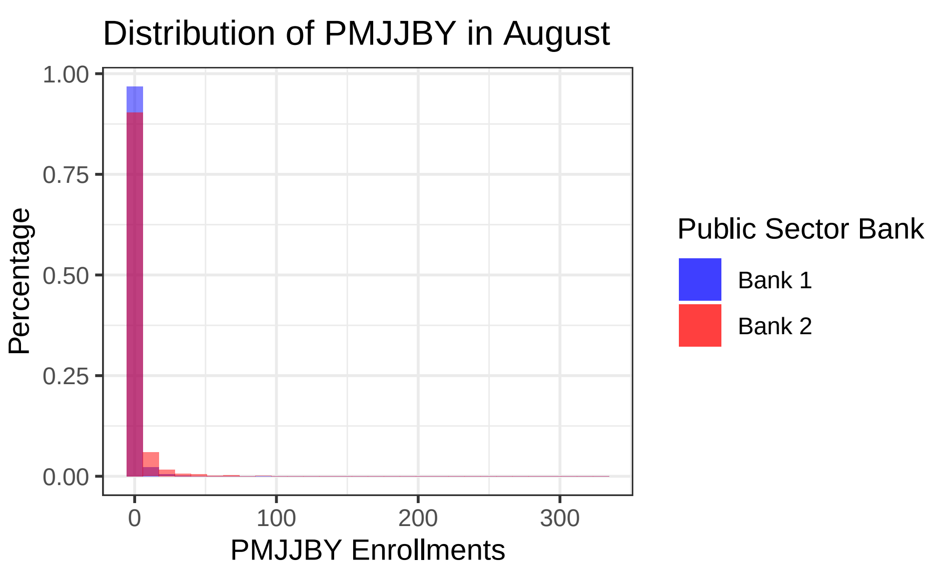

Figure 3: Distribution of PMJJBY Enrollments in the Month Before the Contest

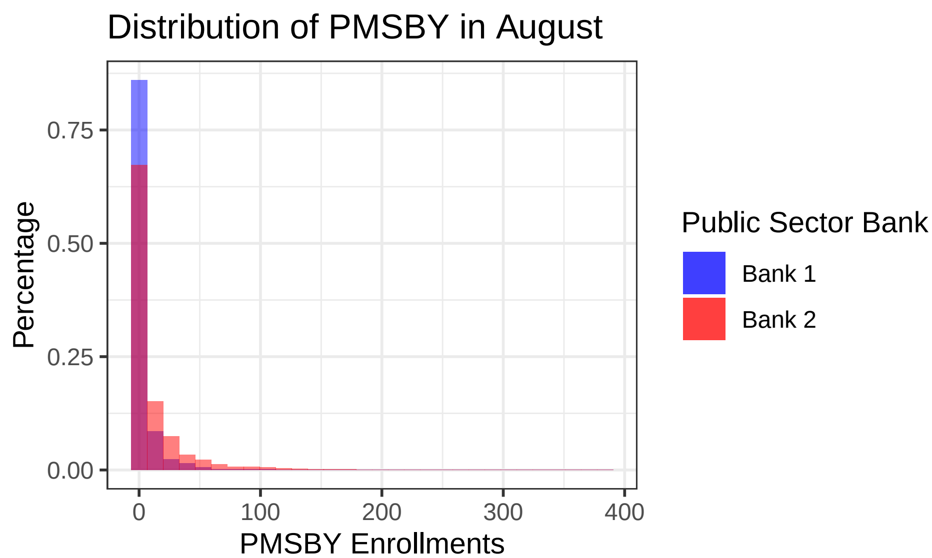

Figure 4: Distribution of PMSBY Enrollments in the Month Before the Contest

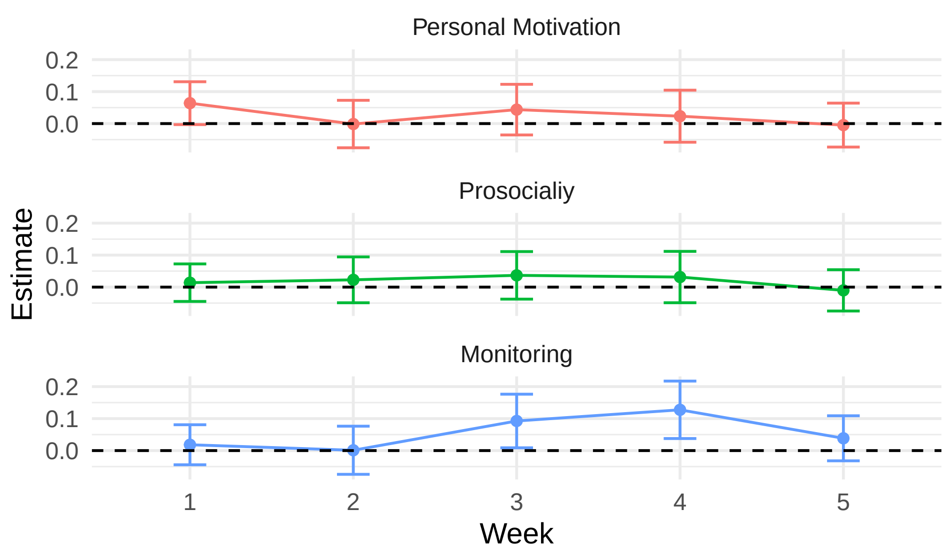

Figure 5: Weekly Estimates for Framings Sent Three Times a Week

Appendix

Table 14: Orthogonality Tables for SMS APY Intervention

	Dependent variable:						
	Control	T1	T2	T3	T4	T5	T6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Zero APY	−0.001	−0.002	0.01	0.002	0.005	−0.004	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
APY Enrollments	−0.0005	0.0002	0.0003	0.001	0.0003	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Transactions	−0.0000	0.0000	0.0000	0.0000	−0.0000	0.0000	−0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	−0.001	0.0001	0.001	−0.0005	0.002**	−0.0003	−0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender (1 if Female)	0.02	−0.02	0.01	−0.002	−0.01	−0.003	−0.004
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Time in network	0.0000	−0.0000	0.0000	−0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.22***	0.14***	0.10***	0.16***	0.08**	0.15***	0.15***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	3,120	3,120	3,120	3,120	3,120	3,120	3,120
R^2	0.001	0.001	0.001	0.001	0.002	0.0002	0.001
Adjusted R^2	−0.002	−0.002	−0.002	−0.002	−0.001	−0.003	−0.002
F Statistic (df = 9; 3110)	0.40	0.21	0.29	0.35	0.65	0.07	0.25

Notes:

This table presents the orthogonality tests for the APY SMS intervention. The F test shows how well observable characteristics fit a model in which treatment assignment is the outcome variable. Note: *p<0.1;**p<0.05; ***p<0.01

Table 15: Orthogonality Tables for SMS PMJJBY/PMSBY Intervention

	Dependent variable:	
	SMS Treatment	
	Bank 1	Bank 2
	(1)	(2)
PMJJBY Enrollments	0.0001	−0.001
	(0.002)	(0.001)
PMSBY Enrollments	−0.0002	−0.0002
	(0.001)	(0.001)
Zero PMSBY	0.001	−0.01
	(0.02)	(0.03)
Transactions	−0.0000	−0.0000
	(0.0000)	(0.0000)
Fixed Deposits	−0.001	−0.001
	(0.003)	(0.01)
Recurrent Deposits	−0.0004	−0.005
	(0.001)	(0.004)
New Accounts Opened	0.0001	−0.0002
	(0.0002)	(0.0003)
Age	−0.001	−0.0003
	(0.001)	(0.001)
Age missing (= 1 if missing)	−0.02	−0.001
	(0.07)	(0.07)
Gender (=1 if Female)	−0.03	0.03
	(0.03)	(0.04)
Time at Agent Network (Days)	0.0000***	0.0000
	(0.0000)	(0.0000)
Time Var missing (= 1 if missing)		0.06
		(0.05)
Constant	0.50***	0.48***
	(0.05)	(0.07)
Observations	3,398	1,781
R^2	0.003	0.01
Adjusted R^2	−0.001	−0.001
F Statistic	0.71 (df = 14; 3383)	0.85 (df = 15; 1765)

Notes:

This table presents the orthogonality tests for the PMJJBY/PMSBY SMS intervention. The F test shows how well observable characteristics fit a model in which treatment assignment is the outcome variable. Note: *p<0.1;**p<0.05; ***p<0.01

Table 16: Effect of Interactions by Week, Bank 1 June

	Total APY Enrollments				
	Week 1	Week 2	Week 3	Week 4	Week 5
	(1)	(2)	(3)	(4)	(5)
Personal Motivation, Once	−0.032	−0.036	−0.003	0.089	−0.013
	(0.079)	(0.117)	(0.096)	(0.154)	(0.077)
Prosociality, Once	0.073	0.008	0.076	−0.045	−0.086
	(0.097)	(0.109)	(0.119)	(0.099)	(0.078)
Monitoring, Once	0.069	0.069	0.048	−0.031	0.042
	(0.080)	(0.117)	(0.119)	(0.096)	(0.084)
Personal Motivation, Three Times	0.339**	0.069	0.107	0.041	0.036
	(0.162)	(0.141)	(0.119)	(0.119)	(0.096)
Prosociality, Three Times	0.083	0.016	0.036	0.033	0.018
	(0.085)	(0.094)	(0.091)	(0.091)	(0.089)
Monitoring, Three Times	0.109	0.015	0.254*	0.466**	0.122
	(0.119)	(0.102)	(0.136)	(0.184)	(0.096)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	3,120	3,120	3,120	3,120	3,120
R^2	0.184	0.266	0.239	0.226	0.260
Adjusted R^2	0.083	0.175	0.145	0.130	0.169

Notes:

This table presents the results from estimating equation 3, where the outcome variable is total Atal Pension Yojana enrollments at the end of each of the 5 weeks. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 17: Effect of SMS on PMJJBY Enrollemnts, Bank 1

	IHS of PMJJBY Enrollments		PMJJBY Enrollments	
	(1)	(2)	(3)	(4)
SMS	0.058**	0.051**	0.314**	0.274*
	(0.025)	(0.025)	(0.147)	(0.157)
Stratification fixed effects	Yes	Yes		
District fixed effects	No	Yes		
Controls	No	Yes		
N	3,398	3,398	3,398	3,398
R^2	0.243	0.489	0.092	0.292
Adjusted R^2	0.242	0.418	0.090	0.194

Notes:

This table presents the results from estimating equation 7, where the outcome variable is total PMJJBY enrollments at the end of the intervention. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 18: Effect of SMS on PMSBY Enrollments, Bank 1

	IHS of PMSBY Enrollments		PMSBY Enrollments	
	(1)	(2)	(3)	(4)
SMS	0.045	0.088**	1.035*	1.345**
	(0.043)	(0.041)	(0.625)	(0.607)
Stratification fixed effects	Yes	Yes		
District fixed effects	No	Yes		
Controls	No	Yes		
N	3,398	3,398	3,398	3,398
R^2	0.548	0.711	0.198	0.416
Adjusted R^2	0.548	0.671	0.197	0.335

Notes:

This table presents the results from estimating equation 7, where the outcome variable is total PMSBY enrollments at the end of the intervention. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 19: Effect of SMS on PMJJBY Enrollemnts, Bank 2

	IHS of PMJJBY Enrollments		PMJJBY Enrollments	
	(1)	(2)	(3)	(4)
SMS	−0.017	0.051	−0.217	0.058
	(0.039)	(0.036)	(0.256)	(0.268)
Stratification fixed effects	Yes	Yes		
District fixed effects	No	Yes		
Controls	No	Yes		
N	1,781	1,781	1,781	1,781
R^2	0.130	0.552	0.049	0.434
Adjusted R^2	0.127	0.445	0.046	0.298

Notes:

This table presents the results from estimating equation 7, where the outcome variable is total PMJJBY enrollments at the end of the intervention. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01

Table 20: Effect of SMS on PMSBY Enrollments, Bank 2

	IHS of PMSBY Enrollments		PMSBY Enrollments	
	(1)	(2)	(3)	(4)
SMS	0.005	0.018	−0.186	−0.057
	(0.057)	(0.054)	(0.631)	(0.674)
Stratification fixed effects	Yes	Yes		
District fixed effects	No	Yes		
Controls	No	Yes		
N	1,781	1,781	1,781	1,781
R^2	0.361	0.630	0.167	0.466
Adjusted R^2	0.359	0.541	0.164	0.337

Notes:

This table presents the results from estimating equation 7, where the outcome variable is total PMJJBY and PMSBY enrollments at the end of the intervention. Heteroskedasticity-robust standard errors are reported in parenthesis below the coefficients. Number of transactions, APY, PMSBY and PMJJBY enrollments are all presented using the inverse hyperbolic sine transformation. Note: *p<0.1;**p<0.05; ***p<0.01