When Transparency Fails: Financial Incentives for Local Banking Agents in Indonesia*

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Abstract

We study the effect of raising the *level* and the *transparency* of financial incentives offered to local agents for acquiring clients of a new banking product on take-up. We find that paying agents higher incentives increases take-up and usage, but only when the incentives are unknown to prospective clients. When disclosed, higher incentives instead have no effect on take-up and usage, despite greater agent effort. This is explained by the financial incentives conveying a *negative signal* about the reliability and trustworthiness of the product and its providers to prospective clients. Organizations designing incentive schemes should therefore pay attention to both the level and the transparency of such incentives.

JEL Codes: J31, D84, M52, O14, G28

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1 Introduction

The delivery of new technologies to rural populations in developing countries is often decentralized and increasingly delegated to local delivery agents (Mansuri and Rao, 2012; Bandiera et al., 2022). Technology adoption crucially depends on the local delivery agents being motivated enough to promote the product in their community but also on the community having enough trust in the local agent, such that the agent's effort translates into higher take-up. To maximize adoption, it is thus essential to carefully consider how to incentivize local agents to exert more effort but also how to build trust in the agent and in the product. In this paper, we study how the *level* and the *transparency* of the financial incentives offered to local agents for acquiring clients of a new branchless banking product affect adoption. We test whether raising financial incentives affects agents' effort and customers' trust differently depending on whether incentives are public (i.e., disclosed to the community) or private, and how this ultimately impacts the take-up and usage of the product.

When disclosed, agent's financial incentives can affect the technology adoption through two main channels: directly, by increasing agent effort (*supply-side effect*) but also indirectly, through a signaling effect that impacts potential clients' perceptions and trust levels (*demand-side effect*). In contexts where technologies have unknown attributes and where trust in the agent or in the product is limited, financial incentives offered to local agents to attract new users can affect demand by conveying a signal about the quality of the product or the intentions of the agent (Benabou and Tirole, 2003). Higher incentives can, for instance, be interpreted as a signal that the agent has a high opportunity cost and is of high ability, or that the product's provider is successful (thus potentially reinforcing the product's demand). Alternatively, higher incentives can be interpreted as a signal that the agent is primarily motivated by earning money (as opposed to pro-social reasons), willing to take advantage of an uninformed consumer, and untrustworthy (thus hampering the product's demand).[1]

[1]This is an extension of the well-known idea that changes in the price of a new product can change people's perception of it (e.g., its quality), and this signal can affect consumer decisions (Milgrom and Roberts, 1986).

If such signaling effects are present, the ability to boost take-up by raising agents' financial incentives crucially depends on the transparency of the incentives – i.e., the extent to which potential users are aware of the agent's compensation level – and how the signal is interpreted. If incentives are private information (known by the agent but not the community), raising their level can have a positive supply-side effect on take-up by prompting agents to exert more effort without triggering any demand-side signaling effect. If incentives are public information (known by the agent *and* the community) instead, the effect of raising them on take-up is ambiguous. If higher incentives convey a positive signal about the product to potential customers, disclosing their level should boost take-up even more. In contrast, if they convey a negative signal about the product, disclosing their level may deteriorate demand perceptions and trust, and attenuate (or even reverse) the positive supply effect.

Using experimental variation in the *level* and the *transparency* of incentives paid to agents responsible for introducing and promoting branchless banking products in rural Indonesia, we find that higher financial incentives increase the take-up and usage of these products. This only holds, however, when financial incentives are unknown to potential clients (private information). In villages where financial incentives are disclosed to potential clients (public information), raising incentives instead has no effect on take-up or usage, even though agent's effort increases. We show that this is explained by financial incentives conveying a *negative signal* about the products, the agent, and the bank, thereby reducing potential clients' trust.

These results corroborate the idea that in contexts with limited information and low trust, financial incentives can affect adoption through a demand-side signaling effect (change in demand perceptions) when they are disclosed. In such settings, organizations must carefully consider the signals financial incentives send to potential clients and thus also the extent to which their employee's incentives are disclosed, as this can affect trust and shape the demand for their products. To maximize trust and take-up, we show that organizations should opt either for high incentives that are not publicized or low incentives that are publicized, but should avoid combining higher (lower) incentives with more (less) transparency.

Our study takes place in rural East Java (Indonesia), a context that is ideally suited to studying whether financial incentives affect demand perceptions through a signaling channel. The population is highly unbanked, branchless banking is non-existent (therefore the product's attributes are unknown) and the level of trust in financial institutions is limited. Such characteristics mean that potential customers will rely on different heuristics (e.g., agent's incentive level) when evaluating the products' benefits and their willingness to adopt them.

The experiment focuses on 401 rural villages where our partner bank was expanding its branchless banking activities. Each village is served by a local agent, who is tasked with promoting two new financial products – an interest-bearing savings account and a digital wallet – and subsequently helping customers deposit and withdraw money from the accounts; thus meaning that they do not need to travel to a more distant branch office or ATM. Similar to other settings where branchless banking has been introduced, agents are business owners with an existing clientele, who are paid a commission for each new client who signs up for the financial products as well as for each subsequent transaction.

Our experimental design has two layers. The first layer introduces exogenous variation in the *level* of the incentives paid to the agents. In the *low incentives* treatment, agents are paid 2,000 Indonesian Rupiah (IDR) (0.14 USD) for each customer who signs up for a savings account (the status quo), while they are paid 10,000 IDR (0.71 USD) in the *high incentives* treatment. In both treatments, agents earn the same commission for each cash deposit or cash withdrawal and prices paid by the consumers remain unchanged. The high incentives treatment is thus meant to incentivize agents to acquire more customers relative to the low incentives treatment but provides no direct incentive to increase the products' usage per customer.

Stratifying by the incentive level, the second layer of the experiment introduces exogenous variation in the *transparency* of the incentives paid to the agents for acquiring new clients. In the *public incentives* treatment, potential customers are informed about the agent's incentive level while in the *private incentives* treatment this information is not disseminated.[2]

When incentives are private, the difference in take-up in the high vs. low incentives treatment captures the supply-side effect of incentives. That is, the effect of higher incentives on take-up due to *agent's higher effort levels*, where any potential signaling effect of incentives (demand-side effect) is shut down by keeping this information private. When incentives are public, the difference in take-up between high vs. low incentives instead captures the *combination* of the supply- and demand-side effects, i.e., the change in the agent's effort and the change in demand perceptions due to the signaling effect. The difference-in-difference estimator thus quantifies the demand-side effect of higher incentives separately from the pure supply-side effect.

We find that raising the level of the incentives has diverging effects on take-up and usage depending on whether the incentives are disclosed to the community or not. When they are *not* disclosed (private information), raising the level of the incentives more than triples the take-up of new financial products one year and a half after their introduction (from 0.6% to 2.7%). In line with an increase in agent effort, data collected from potential clients show that agents in the high incentives treatment are 2.7 times more likely to have offered them the products than in the low incentives treatment. Raising incentives not only affects take-up, but also increases the usage of the products: the total amount of deposits/withdrawals, account balance, and savings increase by 18-20%.

When incentives are disclosed (public information), raising their level has a precise zero effect on the take-up or usage of the new financial products. Interestingly, this is not explained by

[2]The experimental design shuts down any selection effects of the incentives. We do so by sharing information about the level of the incentives for attracting new customers after the agents accepted the position, and by never explicitly telling the agent about pay transparency (or lack thereof). See Section 2.2 for more details.

agents not responding to the higher incentives. In fact, higher incentives still prompt higher agent effort, even when they are public, but this additional effort does not translate into higher take-up or usage. We show that this is due to a signaling effect. Using data collected on the perceptions of potential clients at endline, we find that higher incentives reduce trust in the products, the agent, or the bank when they are disclosed. Consistent with a signaling effect, this effect is stronger for individuals who did not know the agent, did not trust the agent's financial advice, or were unfamiliar with branchless banking at baseline.

We note that the take-up of branchless banking is limited in our context, but it increases over time. One year and a half after the experiment, the take-up rate is 1.3% for the average respondent in our study and 2.7% in the high $\times$ private treatment where take-up is the highest. The take-up rate nearly triples two years later, reaching a 3.6% adoption rate across all respondents of our study and a 7.4% adoption rate in the high $\times$ private treatment. The level and the time pattern of adoption are similar to that of other financial products in low- and middle-income countries.[3]

Our study contributes to different strands of the literature. First, we contribute to a recent and growing literature studying the role of trust in the decentralized delivery of technologies (Cole and Fernando, 2021). In the financial sector, where the bank and/or the agent manage clients' assets, trust has been shown to play a critical role in the adoption of financial products (Breza, Kanz, and Klapper, 2020; Mehrotra, Somville, and Vandewalle, 2021; Bachas et al., 2021). We contribute to this literature by testing whether the level and the transparency of

[3]Figure A.1 presents data from the Global Findex Database, depicting the proportion of individuals aged 15 or older who claim to have used a mobile money service in the previous year. The data is divided into four categories of countries: (i) all countries worldwide, (ii) low and middle-income countries, (iii) low and middle-income countries in the East Asia and Pacific region, and (iv) Indonesia. The data, collected in 2014, 2017, and 2021, demonstrates a significant rise over time in the adoption of mobile money across all groups. This increase parallels the growth in branchless banking uptake in our area of study. The uptake of branchless banking in our context, as recorded in 2018 and 2021, was 1% and 4% respectively on average (3% and 7% in the high$\times$private treatment). These figures are comparable to the adoption rates of mobile money in low- and middle-income countries in the East Asia and Pacific region, which were 1% in 2017 and 5% in 2021. However, these rates fall short of the corresponding uptake rates in low- and middle-income countries on other continents, such as Africa, which saw rates of 5% in 2017 and 12% in 2021. Note that the Findex data does not offer exhaustive information about branchless banking products, but only on mobile accounts.

agents' incentives impact prospective clients' trust. We show that revealing agent's incentives deteriorates clients' trust in the agent, the product, and the bank (relative to not disclosing the incentives) if the incentives are high, and this hampers demand. If the incentives are low, revealing their level instead improves customers' trust and boosts demand. These results highlight that customers' trust is influenced by the knowledge of the level of agent's incentives and is key in understanding the take-up of branchless banking.

Second, to the best of our knowledge, our paper is the first to explore the combined effect of varying the *level* and the *transparency* of incentives on take-up. In doing so, we complement papers that have studied the isolated effect of varying the level of agents' incentives while holding transparency fixed (Aubert, de Janvry, and Sadoulet, 2009; Giné, Mansuri, and Shrestha, 2020). These papers document diverging effects of financial incentives on take-up. The results of this paper indicate that these seemingly contradictory effects may potentially be explained by differences in the level of transparency across contexts. We also complement papers that have studied the isolated effect of disclosing incentives to prospective customers while holding the level of the incentives fixed (Mullainathan, Nöth, and Schoar, 2012; Anagol, Cole, and Sarkar, 2017). In a study close to ours, Anagol, Cole, and Sarkar (2017) show that life insurance agents in India provide poor advice to customers in order to maximize their commissions, but that this misbehavior is muted when their commissions are disclosed. We shed light on a different mechanism through which the disclosure of high-powered incentives can affect the take-up of a product: the signaling effect of financial incentives.

Finally, we also contribute to the literature that explores the impact of new digital financial products in developing countries. Recent research in this area has documented positive effects of mobile money on aspects such as user consumption and poverty alleviation (Suri and Jack, 2016; Suri, 2017), as well as migration and remittances (Batista and Vicente, 2021), and risk sharing (Jack and Suri, 2014; Blumenstock, Eagle, and Fafchamps, 2016; Riley, 2018; Batista and Vicente, 2020). Our study, however, centers on branchless banking, a system that, unlike mobile money, offers more complex financial products, necessitates transactions via an agent, is directly linked to a bank, is regulated, and has only been recently introduced in numerous countries. Recent studies by Bharadwaj, Jack, and Suri (2021); Bastian et al. (2018) indicate that branchless banking products, such as credit lines or savings accounts, increase household resilience and savings. Our analysis delves into how the design of financial incentives for branchless banking agents affects the adoption and utilization of these products, factors which are vital for the aforementioned positive effects to occur.

2 Background and Experimental Design

2.1 Background

Compared to other low- and middle-income countries in East Asia and the Pacific, Indonesia has a relatively low penetration of financial services. In 2017, 49% of Indonesian adults had a bank account, compared to 71% in other non-high-income countries in Eastern Asia Pacific (Demirguc-Kunt et al., 2018). In East Java specifically, just 43% of the households we surveyed at baseline reported having made a transaction with any bank in the month prior to the interview, while only 26% had a savings account. Moreover, 40% of the household respondents reported having no trust in banks. This lack of trust in the financial sector – which emerged in the aftermath of the Asian economic crisis of the late nineties (Nasution, 2000) – is considered one of the key constraints to financial inclusion in Indonesia (Soedarmono, Prasetyantoko, and Sitorus, 2017).

In response to this issue, in 2014 the Government of Indonesia adopted a law establishing banking services without the need for branch offices, called "branchless banking." The Indonesian model of branchless banking works similarly to that used in many other countries, where village-based agents offer basic banking services that are normally performed at more distant branch offices or ATMs (Mas and Kumar, 2008; Siedek, 2008).

We collaborated with one of the largest banks in Indonesia (henceforth referred to as *the bank* for confidentiality reasons), which began branchless banking activities shortly after the passing of the 2014 law, and was rolling out branchless banking in East Java at the time of our study. Specifically, the bank hires local branchless banking agents to promote basic interest-bearing savings accounts with no opening or maintenance fees, which can be used for savings, transfers, or payments. The accounts are intended to supplement a digital wallet product (also offered by the agents) that provides a narrower range of services, does not pay interest, and is not insured by the government.[4] Note that the interest-bearing savings and e-wallet accounts differ from typical mobile money services because they are explicitly linked to a bank and regulated. All transactions involving the interest-bearing savings account are facilitated through an agent. However, transactions to and from the e-wallet account can be conducted without an agent's involvement.

Branchless banking agents are business owners with an existing clientele (e.g., shop, restaurant, or cell phone top-up station owners), who are asked to promote the savings account and the digital wallet in their villages as a secondary job. They are responsible for (1) identifying and enrolling new clients, and (2) performing cash deposits and making cash disbursements to/from customers accounts. These services are delivered through an online platform that the agent can access from a phone or computer with internet access.[5]

The agents' compensation is entirely commission-based: they are paid a commission for every new client who opens an account and for each transaction made and receive no fixed salary. The commission is typically unknown to other individuals in the community. In the next section, we discuss in greater detail the level and transparency of the incentive scheme.

Agents are recruited by the bank among villagers who: (1) are the owners of a centrally

[4] Unlike the digital wallet, the savings account pays an interest of 0.15% and is insured by the government through Lembaga Penjamin Simpanan (the Indonesia Deposit Insurance Corporation). It allows a maximum balance of 20 million IDR and a monthly maximum cash withdrawal or transfer of 5 million IDR.

[5] The service is more reliable in villages with better signal.

located business, (2) are clients of the bank, (3) are mostly present at their business premises, (4) have a good reputation in the community (as confirmed by the village authorities), and (5) are able to demonstrate sufficient financial liquidity. Once hired, agents receive three one-to-one training sessions of 2.5 hours each, during which they learn about the financial products to be promoted, the online system to be used, and marketing techniques.

National data from Indonesia reveals an S-shaped adoption rate for branchless banking, a pattern typically observed with the introduction of new technologies possessing network externalities. The adoption rate initially stagnated at 4.7% up to a year post-introduction, before experiencing a tenfold increase three years later (Kantar, 2018; Barquin, de Gantès, and Duhita Shrikhande, 2019).[6] Consistent with Indonesian national data, we find that the adoption rate of branchless banking in our study areas is low at one and a half years post-introduction (the period at which we estimate effects), but nearly triples two years later. As shown in Figure A.1 and explained in Footnote 3, this pattern of adoption parallels the one of mobile money in low and middle-income countries.

2.2 Experimental Design

Our study includes 401 rural villages in five regencies (Tuban, Bojonegoro, Gresik, Ngawi, and Lamongan) of East Java, in which branchless banking activities were introduced by the bank in November 2016. In each village, one branchless-banking agent was recruited and trained by the bank with the support of the research team (to ensure compliance with the

[6] Adoption is defined as the number of people using an account, even if they do not own one. Seminal works on technology diffusion by Beal, Rogers, and Bohlen (1957); Griliches (1957) argue that the adoption of new technologies often follows an S-shaped curve, and is particularly slow in environments where information transmission is limited, as in our case. In Africa, where mobile money is more prevalent than branchless banking, user proportions vary significantly across countries. There is a high penetration rate (ranging from 14% to 20%) in Southern and Eastern African countries, like Kenya, where these products were introduced earlier (Jack and Suri, 2014). However, a considerably lower penetration rate (from 0% to 4%) is seen in countries where these products were introduced more recently, such as Niger, Nigeria, Burkina Faso, Togo, Congo, Benin, Cameroon, Guinea, Sierra Leone, Ethiopia, Malawi, and Burundi (Infomineo, 2017). Regrettably, data on adoption rates of branchless banking products are not available for multiple countries.

research protocols).[7]

The experiment is designed to test the effect of raising the *level* and the *transparency* of financial incentives paid to branchless banking agents for the adoption of the new products. To this end, the experiment randomly assigned the 401 newly recruited agents into one of four treatment groups: high × public incentives (N=139), high × private incentives (N=57), low × public incentives (N=137), and low × private incentives (N=68), with the last treatment group being the status-quo.

Each treatment varies along two dimensions: (1) the *level* of the incentives (*high or low*), and (2) whether these incentives are *public or private information* for potential clients. The randomization is stratified by regency and by three village-level characteristics expected to predict take-up of the financial products: above-median distance between the village and the closest branch of the bank, above-median number of households, and whether there is another bank offering branchless banking within the village. The public treatment is over-sampled relative to the private treatment in order to maximize statistical power in identifying the signaling effects of the high vs. low incentives treatment, which materialize only in the public treatment.

High vs. Low Incentives

In the low incentives treatment, agents are paid 2,000 IDR (0.14 USD) for each customer who signs up for a savings account (the status quo). In the high incentives treatment, agents are paid 10,000 IDR (0.71 USD). In both treatments, the commission is paid conditional on the client keeping a minimum balance of 20,000 IDR (1.42 USD) in the account for at least two weeks. This condition was imposed to limit potential collusion between the client and the agent (e.g., a customer signing up for an account and then immediately closing it).

[7] Agent recruitment was conducted in two batches: November 2016 - February 2017 when 107 agents were enlisted, and July – November 2017 when an additional 294 agents were added.

In both treatments, agents earn the exact same commission for (i) customers who sign up for the digital wallet account, and (ii) cash deposits or cash withdrawals in the saving account and the digital wallet.[8] Our treatments are therefore meant to incentivize agents to acquire more customers, rather than to increase usage of the products. The fees charged to customers for each transaction are kept constant across treatments. Customers pay 3,000 IDR (resp., 5,000 IDR) for withdrawals below (resp., above) 200,000 IDR, while deposits are free.

To put the size of the incentives in context, in the high (resp., low) incentives treatment, agents' earnings amount to the average monthly food consumption in East Java (425,000 IDR, 2015 Central Bureau of Statistics) if 15 (resp., 22) customers sign up for the savings account and each performs 5 deposits and 5 cash withdrawals per month. The average agent in our sample would have to sign up at least 455 clients for branchless banking to become her main source of income. This number is much higher than what we observe in our data.

Public vs. Private Incentives

The experiment randomizes whether households are told or not about agent's incentives: incentives were not publicized in the private incentives treatment (status quo), while they were publicized in the public incentives treatment. Because agents are new in the villages, households in our study are unlikely to be aware of the level of the incentives paid to the agent if this is not explicitly revealed to them. More precisely, we surveyed a random sample of entrepreneurs in our baseline survey and showed them an information leaflet at the end of the survey. The same information was contemporaneously disclosed to other entrepreneurs in the village by phone.[9] In the private incentives treatment, the leaflet contained information

[8] Agents earn 5,000 IDR for each customer who signs up for the digital wallet account. They are also paid 1,000 IDR for each cash deposit above 10,000 IDR, 2,500 IDR for each cash withdrawal under 200,000 IDR, and 4,000 IDR for each cash withdrawal above 200,000 IDR. These commissions on cash deposits and withdrawals apply for both the savings account and the digital wallet, and do not vary across treatments.

[9] Before fielding our baseline survey, we collected a listing of entrepreneurs in the village (average of 62 entrepreneurs per village). A random 12 entrepreneurs were selected to be surveyed at baseline and endline, while the rest were not surveyed. (Refer to the next section for details on this sampling strategy.) All individuals in our listing were given the information on the leaflet by the same enumerators, either in person (for those surveyed) or by phone (for those not surveyed).

about the new savings account, the fees charged for deposits and withdrawals, and the identity of the agent (see Figure A.2a). In the public incentives treatment, the leaflet contained the exact same information but also revealed the piece-rate incentive earned by the agent for each client who signs up for the savings account: 2,000 IDR in the low $\times$ public treatment and 10,000 IDR in the high $\times$ public treatment (see Figure A.2b and A.2c).

In both treatments (public and private), the information disclosed on the leaflet was read to the respondent by a trained enumerator who orally also revealed the name and surname of the agent in the third section of the leaflet and the account's conditions (fees, deposit, interest rates) in the last section. Thus, the only difference in the information provided to potential clients across treatments is the one on the agent's incentives for acquiring new clients, while information on the identity of the agent and the account's conditions is held constant.

Two more features of our experimental design are worth noting. First, we deliberately shut down any selection effect of the incentives. All agents were recruited in the same exact way in all four treatments, by advertising the commissions paid per transaction (same across treatments) but without any mention of the level or transparency of the commission per new client sign-up (which varies across treatments). The existence of the sign-up commission and its amount were only revealed to the agents once they had accepted the job and signed a contract with the bank. Unsurprisingly, no agent dropped out after learning about the existence of the commission.[10] Meanwhile, to make the study environment as natural as possible, the transparency of the incentives was never revealed by us to the agents, though they may eventually have learned about it from other people in their village.

Second, throughout the experiment, we minimized spillovers across treatments by limiting interactions between agents. Training sessions were, for example, organized one-to-one, while we avoided any joint meetings.

[10] Nine of the original 401 agents dropped out before they signed the contract and before they received information about the commission. These agents were replaced with the next suitable candidate in the village.

2.3 Data

Baseline Survey Data (November 2016 - November 2017) Upon completion of the agent training, we surveyed all agents (except one, who declined to be interviewed, N=400) right after they had accepted their position. We also simultaneously surveyed a sample of 12 potential clients per village (N=4,828), chosen randomly from a listing of entrepreneurs.[11] These potential clients – who we will refer to as "household respondents" – were asked about their socio-economic background, financial inclusion, knowledge, and usage of the financial products, etc. We also collected baseline data on basic village characteristics (population, distance to bank branches, etc.) by interviewing relevant local authorities.

Endline Survey Data (November 2018 - January 2019) We interviewed the same respondents from our baseline survey again at endline. The endline survey was conducted between November 2018 and January 2019, and thus we evaluate the impacts of our treatments 14 to 21 months after the financial products were first introduced in the villages. Agents were asked about task allocation and investment decisions related to their branchless banking job. Household respondents were asked the same questions as in the baseline survey. Additionally, they were asked about (i) take-up of the branchless banking products, (ii) the number of times the products were advertised to them by the agent, and whether they learned about the products through the agent (used as proxies for "agent effort", among other variables), (iii) their level of trust in the product, agent, or bank, and the extent to which they perceived the product as reliable. These extra questions were asked at endline only, since branchless banking was mostly unavailable in the village at baseline. Attrition was minimal at endline: only 16 out of 4,828 household respondents attrited.

We complement endline survey data on take-up with data on product usage that the bank

[11] Branchless banking offers products with network externalities and thus the bank wanted to first target early adopters. A consumer survey we conducted indicates that entrepreneurs are three times more likely to adopt branchless banking products than non-entrepreneurs. The average community in our sample is composed of 12.6% entrepreneurs.

shared with us. For each household in our endline survey, we know (i) the number of transactions (cash deposits and withdrawals) performed from the financial products, (ii) the amount of each of these transactions, and (iii) the total balance in the financial products at endline.

We also have access to "long-term" administrative data from the bank on take-up and transactions for the period January-October 2021 (38 to 50 months after the start of the intervention). We describe and analyze these data in Section 6.

2.4 Descriptive Statistics and Balance Checks

Baseline summary statistics and balance checks at the agent/village and household level are presented in Table A.1. The average village in our sample is composed of 964 individuals and is 12km away from the closest bank (Panel A). 67% of the villages have good internet coverage, which is essential for the proper and reliable functioning of branchless banking. Among the agents and household respondents, 48% and 59% are women, respectively (Panels B and C). The large majority of both groups (85% and 95%) are involved in a non-farm business. Though almost everyone owns a phone, only 54% of the agents and 27% of the household respondents possess a laptop. This is thus a context where a non-trivial share of branchless banking transactions is made by phone rather than by computer. Agents tend to be more educated than the average household respondent: 43% of the agents have completed tertiary education compared to only 12% of the household respondents. Only 8% of the households had ever heard about branchless banking, confirming that this technology is new to potential clients in the villages we study.

Most of the variables described above are balanced across treatments. In Table A.1 (column 4), we test for the equality of means across the four treatment groups using a joint F-statistic. In columns (5)-(8), we present balance checks for pairwise comparisons: high $\times$ private vs. low $\times$ private incentives treatment (column 5), high $\times$ public vs. low $\times$ public (column 6), high $\times$ public vs. high $\times$ private (column 7), low $\times$ public vs. low $\times$ private (column

8). Consistent with randomization, only six out of the 112 pairwise treatment comparisons presented in Table A.1 are unbalanced, with a p-value below 0.1. The means and standard deviations of each variable by treatment groups are reported in Table A.2.

3 Empirical Strategy

Where there is imperfect information about a product or technology, financial incentives can affect adoption by motivating agents to exert more effort (supply effect) but also by acting as a signal that influences demand-side perceptions of the trustworthiness and quality of the product, the agent, and/or the bank. We will refer to the latter as the "demand effect" or the "signaling effect."

By creating variation in both the *level* and the *transparency* of the incentives, our experiment aims to separately identify these supply and demand effects. To do so, we will use the following empirical model throughout the paper:

$$y_{ij} = \beta_0 + \beta_1 High_j \times Private_j + \beta_2 High_j \times Public_j + \beta_3 Low_j \times Public_j + Z_j'\gamma + \epsilon_{ij}. \quad (1)$$

y_{ij} is an indicator for whether the potential client i in village j signed up for any of the new branchless banking products. $High_j (Low_j)$ and $Private_j (Public_j)$ are indicators for whether the agent in village j was assigned to the high (low) incentives treatment, and whether potential clients in the village were not informed (informed) about the agent's compensation. The excluded category corresponds to the status-quo: $Low_j \times Private_j$. Z_j are the stratification variables discussed above. ε_{ij} are errors clustered at the level of treatment assignment, the village.

When incentives are private, the difference in take-up in the high vs. low incentives treatment is estimated by $High_j \times Private_j$ (β_1). This estimate captures the supply-side effect of incentives. Namely, the direct effect of higher incentives due to the *agent's higher effort level*, in the absence of any signaling effect. In line with most labor supply frameworks, we expect higher financial incentives to increase the amount of effort agents exert in promoting the new products. This could, in turn, favorably influence how clients perceive the products' net benefits, and potentially increase their take-up.

When incentives are public information, the difference in outcomes in the high vs. low incentives treatment is equal to $High_j \times Public_j - Low_j \times Public_j$ $(\beta_2 - \beta_3)$. This estimate captures the combination of the supply-side effect – i.e., the change in agent effort – and the demand-side effect – i.e., the change in client perceptions generated by the signaling effect of the incentives. The difference-in-difference estimate $((\beta_2 - \beta_3) - \beta_1)$ quantifies the demand-side effect (i.e., the signaling effect of higher incentives) net of the supply-side effect.

The direction of the demand-side effect is theoretically ambiguous. On the one hand, learning that an agent earns a high commission could be interpreted as a signal that she has a high opportunity cost and hence is of high ability (e.g., she provides better services or is well-positioned to assess the potential benefits of the product for the user). In a similar vein, higher incentives could indicate that the bank is successful (and hence able to pay high incentives) thanks to the good quality of the products it offers. This positive interpretation of the signal would result in financial incentives boosting the product's demand, reinforcing the supply-side effects (that is, $(\beta_2 - \beta_3) - \beta_1 > 0$).

On the other hand, learning that an agent earns high commissions could be interpreted as a signal that the agent is primarily motivated by earning more money (as opposed to pro-socially motivated), and hence more likely to take advantage of an uninformed consumer (Bénabou and Tirole, 2006). This would reinforce the already low levels of trust in the financial sector and its products. Likewise, a bank that pays high incentives may be perceived as offering low-quality products, necessarily requiring a more motivated marketing staff. This negative interpretation of the signal would hamper the product's demand, thus attenuating the supply effect (that is, $(\beta_2 - \beta_3) - \beta_1 < 0$). Under such circumstances, the overall effect of higher financial incentives on take-up would ultimately depend on the relative size of the supply- and the demand-side effects.

Importantly, the signals conveyed by the financial incentives can indirectly generate a supply-side response. If, for example, high $\times$ public incentives convey a negative signal, agents may internalize that the return to promoting the bank's products is diminished or may feel uncomfortable approaching a potential client out of concern that they may be perceived as wanting only money. Agents might react by reducing the amount of effort exerted in promoting the bank's products, either because they perceive the marginal return of this activity to be lower or because they may have to work harder in their business to counteract the signaling effect (which may crowd out time spent promoting the bank's products). To counteract the signaling effect, they may also modify their sales strategy (e.g., becoming more "aggressive" in their approach). Alternatively, they might change the type of potential client to whom they promote the product (e.g., targeting only friends). In Section 5.1, we show that this indirect supply-side response (triggered by a change in demand's perceptions) is present in our context, but is limited.

Finally, we use Equation 1 to evaluate the independent effect of publicly providing information about agents' incentives on take-up. More precisely, the coefficient for $Low_j \times Public_j$ allows us to assess whether it is in the bank's best interest to preserve the privacy of *low* incentives or whether they should make them public information. Similarly, the coefficient for $High_j \times Public_j - High_j \times Private_j$ allows us to assess whether the bank should preserve the privacy of *high* incentives or not. If incentives convey a negative (resp., positive) signal, we would expect public incentives to achieve higher (resp., lower) adoption relative to private incentives only if they are low (resp., high).

Identifying Assumptions

The identification of the supply- and demand-side effects of financial incentives rely on two assumptions. The first is that potential clients have limited information about agents' incentives in the private incentives treatment. This ensures that any signaling effect of incentives (demand-side) is shut down, and that any difference in outcomes between the high and low incentives treatment can therefore be attributed to the increased effort of the agents (supply-side). We further show in Section 5.2 that potential clients have similar perceptions about agents' earnings in the high × private treatment as in the low × private one.

The second identifying assumption is that agents are equally likely to be the residual claimants of their effort across all treatment groups. This would be violated if, for example, they face higher informal taxation when incentives are public rather than private (Collier and Garg, 1999; Jakiela and Ozier, 2016). That is, if community members demand redistribution upon learning about agents' higher earnings, then public information would reduce the agents' marginal returns to effort and would make them less responsive to an increase in incentives. As a result, the difference-in-difference estimate $((\beta_2 - \beta_3) - \beta_1)$ would capture the reduction in the agent's effort due to informal taxation rather than only due to the incentive signaling effect.[12] Similarly, agents in the high × public incentives treatment may be pressured by adopters to reduce the fees they later charge for depositing or withdrawing money from the accounts. If that were the case, the higher incentive that agents earn for each new account sign-up may be offset by them having to reduce future transaction fees, thus reducing the agents marginal returns in acquiring new customers when incentives are public. If these "redistribution" stories were relevant in our context, we would observe agents exerting less effort with high × public incentives than with high × private ones. We will later show that the difference in the agents' effort in the two treatments is not statistically significant. Moreover,

[12] As explained above, the signaling effect of the incentives impacts client perceptions and, through this, could also affect agent effort. What is important for our identification is that any change in agent effort in the high × public vs. high × private treatment is directly or indirectly generated by this signaling effect only, and not by informal taxation/redistribution.

to corroborate the lack of limited informal taxation and redistribution, we asked household respondents whether they had ever shared the proceeds of a successful business in the form of loans, favors, or gifts with other villagers. Only 3% of the respondents answered that they did so.

4 Results: Take-up and Usage of Financial Products

4.1 Take-up

In this section, we first estimate the effects of our treatments on the take-up of either of the new financial products (the savings accounts or the digital wallet), and then analyze them separately. We estimate the effects at endline, roughly a year and a half after the introduction of branchless banking. Using less granular data, Section 6.1 provides evidence of these effects two years later.

We proceed in two steps. First, we report the average take-up rate per treatment using the raw data in Figure A.3 and Table A.3.[13] We then present the results from Equation 1 in Table 1. The regression coefficients are reported in the bottom panel, while in each row of the top panel, we report: (i) the effect of higher incentives, where this information is private: *(High - Low)* $\times$ *Private*; (ii) the effect of higher incentives, where this information is public: *(High - Low)* $\times$ *Public*; and (iii) the difference-in-difference coefficient: *(High - Low)* $\times$ *(Public - Private)*.

High vs. Low Incentives when Incentives are Private

We start by assessing the effect of raising financial incentives when this information is not made publicly available to potential clients. The first two bars in Figure A.3 and Panel B of Table A.3 show that the take-up rate is 0.6% when incentives are low. When incentives are

[13] Table A.3 shows the raw data for the main outcome variables used in the paper, by treatment arm and testing the differences in means.

high, take-up is 4 times as high, increasing by 2.1 percentage points. The difference between the two means is statistically significant at the 1% level (p-value of 0.002).

Table 1 presents the regression coefficients from Equation 1. Relative to low × private incentives, high × private incentives increase take-up by 2 percentage points (+333%) – see the coefficient *(High - Low)* × *Private*. As we will show in Section 5.1, this increase in take-up is explained by a strong positive effect of financial incentives on agents' effort in promoting the financial products.

Although higher financial incentives cause a large percentage increase in take-up, the overall share of users in the population remains low in both treatments: 7.7 clients per village in the low × private treatment and 22.4 clients per village in the high × private treatment (Table A.3, Panel A).[14] We will later show that in our context, the relatively small *absolute* increase in the take-up of branchless banking accounts is accompanied by an increase in product usage: clients who take up the product end making more transactions, have a higher total account balance and more savings. This suggests that the low take-up rate is unlikely to be explained by the product being of low quality, in which case individuals would not use it after adopting it. As typical with brand-new technologies in poor countries (Beal, Rogers, and Bohlen, 1957; Griliches, 1957), we show in Section 6.1 that the take-up increased over time and that it thus takes time for branchless banking to be more widely adopted.

High vs. Low Incentives when Incentives are Public

The last two bars of Figure A.3 compare take-up with low vs. high incentives when incentives are disclosed to potential clients. Relative to low × public incentives, high × public incentives do not have a significant effect on take-up. Similar results are obtained in Table 1 (second row of column 1): the coefficient *(High - Low)* × *Public* – which represents the effect of raising incentives when they are disclosed to potential clients – is close to zero and precisely

[14] We get these numbers by scaling up the responses from our survey by the inverse sampling probability.

estimated. This indicates that making high incentives public information annihilates the boost in take-up observed when high incentives are kept private.

We conjecture that this occurs because high (resp., low) public incentives convey a negative (resp., positive) signal about the quality of the product, the agent, and the bank to potential clients, which, in turn, causes a contraction (resp., expansion) in the demand for these products. Indeed, the coefficient for *(High - Low)* × *(Public - Private)* – which isolates the demand effect – is negative and statistically significant (third row of Table 1, column 1), and of the same magnitude as the supply effect. We explore this signaling effect in detail in Section 5.2, where we show how potential clients' perceptions change when high or low agent incentives are disclosed.

Private vs. Public Incentives

Thus far, we have studied the causal effect of raising the incentive level with and without pay transparency. We now assess the causal effect of publicly disseminating information about the agent's incentives, holding the incentive level fixed.

As shown in the pink bars of Figure A.3 and in the bottom panel of Table 1, take-up is 1.5 percentage point (281%) higher in the high × private treatment compared to the high × public one. This is consistent with our hypothesis that making information about high incentives public may negatively affect potential clients' perceptions, hence reducing trust and demand for the products.

Interestingly, when incentives are low, the take-up of new technologies appears higher when potential clients are informed about the incentives than when they are not. Though this result is not statistically significant, it does suggest that making low incentives public may convey a *positive* signal, which in turn could boost demand. We return to this point in Section 5.2.

Robustness Checks

Tables A.4, A.5, and A.6 show that the results presented thus far (and all the subsequent main results) are robust to (i) accounting for multiple hypothesis testing, (ii) controlling for all variables that are unbalanced across at least one of the pairwise treatment comparisons at baseline (see Table A.1), and (iii) re-weighting the observations for the sampling probability in each village.[15] The results obtained in these robustness tables are very similar to the main findings.

4.2 Use of Financial Products and Savings

From the point of view of the bank, the agent, and that of general welfare, it is important to analyze the actual usage intensity of the products (which provides revenues to the bank and the agent) and whether they in fact allow clients to increase their savings.

To measure account usage, we employ data recorded by the bank on the total amount involved in cash-in's and cash-out's from branchless banking accounts between baseline and endline, as well as the total balance in these accounts at endline.[16] In addition, we look at yearly savings in the bank's branchless banking account, as reported by household respondents in our endline survey. Because these variables are all expressed in Indonesian Rupiah (IDR), we use inverse hyperbolic sine transformations (IHS) to deal with data skewness, while retaining the zeros (Johnson, 1949; Friedline, Masa, and Chowa, 2015). Marginal effects of the treatments are computed following Norton (2022). The results are presented in columns 2-4 of Table 1.

When incentives are kept private, paying the branchless banking agent a higher incentive for take-up increases product usage: the total transactions amount goes up by 15.2% (3,589.37

[15]Our endline survey covers 12 households per village irrespective of the village size. We re-weight the observations to capture the treatment effect on the average household in our study (more weight to large villages than small ones).

[16]These measures take a value of zero if the household did not open an account and thus capture both the intensive and extensive margins of adoption. The data do not allow us to distinguish between deposits and withdrawals, hence we focus on the combined amount involved in both of these transactions.

IRP), and the total balance increases by 16.7% (3,656.35 IRP). Savings in the branchless banking account also significantly increase by 16.4% (681.32 IRP).[17] The increase in the amount saved in the branchless banking products does not come at the expense of lower savings in other non-branchless banking products (see Table A.7, column 4), and thus represents a net increase in individual savings.

When incentives are made public, paying the branchless banking agents a higher incentive does not impact usage or savings.

4.3 Product-by-Product Analysis

Thus far, we have focused on the take-up and usage of any branchless banking product offered by the bank, whether this be the savings account or the digital wallet. In Table A.8, we analyze the take-up and usage of each of these two products separately. This is important as only the savings account was differentially incentivized across treatments.

Table A.8 shows that higher private incentives increase the take-up and usage of both products, and the effects are of about the same magnitude. This suggests that more effort exerted by the agent in promoting the savings account increases awareness and take-up of *both* products, or makes the agents become more effective at promoting any product (i.e., "higher promotion skills"). In contrast, higher public incentives have no effect on the take-up and usage of either product. This suggests that publicly disclosing the higher incentives for one of the two products negatively affects perceptions about both. This is not surprising: if the higher (resp., lower) incentive generates a drop (resp., increase) in trust in the agent or the bank (as we document in Section 5.2), this should negatively (resp., positively) affect the demand for all products offered by the same agent and the same bank.

Next, we study the effect of our treatments on the take-up of financial products offered by

[17] Consistent with the population being relatively poor, the average saving level at endline is low (4,150 IDR). When we regress the level of savings on the treatments, we find that the high × private treatment raises savings by 24,080 IDR with respect to the control group, though the estimates are noisy.

other banks. One concern is that increased adoption of our partner bank's products could be compensated with a reduction in the take-up of other banks' products, such that overall financial inclusion remains unaffected. Table A.7 leverages data from our household survey and shows that this is not the case: higher private incentives do not reduce the take-up of either branchless banking products offered by other banks (column 1) or other formal non-branchless products (columns 2-3) nor do they reduce the total amount of savings as discussed earlier (column 4).[18]

5 Supply and Demand Effects of Financial Incentives

5.1 Agent Effort

In this section, we study the effect of our treatments on the effort exerted by agents in promoting the bank's new financial products. We do this by leveraging data from our household survey on the interactions between the potential clients and the agent. As before, we present the results using the raw data (Figure A.4 and Panel C of Table A.3) and then using Equation 1 (Table 2). Our main measure of agent effort is the number of times the agent approached potential clients to advertise the branchless banking products, as reported by the households in the endline survey. This measure is highly and positively correlated with the take-up and the usage of the products, as we show in Panel A of Figure A.5.

Figure A.4 shows that when incentives are high, agents approach potential clients more than 4 times as often as when they are low. Interestingly, the increase in agent effort is present both in the private and public treatment, and although it is higher in the former, the difference is not statistically significant. This suggests that the public availability of information about agent compensation affected the effort response to the incentives, but only marginally. This

[18]Table A.7 shows that higher public incentives increase the adoption of more formal financial products (row 2, columns 2-3), though they do not increase the take-up of branchless banking products offered by other banks (row 2, column 1). The higher effort of agents in promoting the bank's branchless banking products in the public treatment thus seems to have positively spilled over into non-branchless banking products (e.g., by making clients more aware of banks), but not into other competing branchless banking products.

is consistent with agents not fully internalizing or reacting to the signaling effect of public information, as well as with the assumption that informal taxation or other "redistribution" stories are limited in our setting.

In Table 2, we estimate Equation 1 and extend the list of outcomes used to measure agent effort. High $\times$ private incentives prompt agents to advertise the products 4.56 times more often to potential clients relative to low $\times$ private incentives (0.20 more times, see column 1). Similarly, we find that households are 2.15 times more likely to have learned about the products from the agent (1.5 percentage point increase, see column 2).[19] Column 3 presents a summary measure (the first principal component) of the two previous indicators of agent effort and shows that it doubles in the high $\times$ private relative to the low $\times$ private treatment. An almost similar boost in agent effort is observed in the high $\times$ public incentives treatment relative to the low $\times$ public incentives treatment. As in Figure A.4, the boost in effort generated by the higher incentives is only marginally affected by whether agent compensation is public or private information, i.e., the coefficient *(High - Low)* $\times$ *(Public - Private)* is not statistically different from zero.

In Table 2, columns 4-6, we study a second dimension of agents' response to financial incentives: their "sales strategy," i.e., whether agents become more "proactive" in promoting the new financial products. To this end, we asked household respondents at endline whether the agent directly approached and encouraged them to take up the products and if they believe the agent did all she could to convince them to do so. We find that agents are 2.7 times more likely to have offered the product to potential clients in the high $\times$ private incentives treatment than in the low $\times$ private one (3.8 percentage points increase, see column 4), and 2.4 times more likely to proactively try to complete the sale (3.3 percentage points increase, see column 5). Results are similar if we use the first principal component of these two "sales strategy" variables (column 6). Again, these effects are not statistically different in the public

[19] This variable takes a value of zero if the household respondent has never heard about the product or if they heard about it from other sources.

and private treatments.[20]

Financial incentives also affect agents' task and investment decisions, as measured by self-reported data from the endline agent survey. The results on tasks are presented in Table A.10.[21] In the high × private treatment, agents are 36% (20.5 percentage points) more likely to report promoting products at the store, 33% (21.5 percentage points) more likely to promote products outside of the store, and 77% (19.2 percentage points) more likely to support clients with sign-ups relative to the low × private treatment (columns 1 to 3). They are not significantly more likely to report dealing with client complaints, providing cash for clients' transactions, or assisting in product usage (columns 4 to 6). These results are consistent with agents in the high incentives treatment being more incentivized for take-up but equally incentivized for product usage.

The results on investments are presented in Table A.11. Higher private incentives did not prompt agents to upgrade their computers or phones. They did however double the likelihood (17.5 percentage points) that agents invested in a data plan that gives more reliable internet access (columns 1-3). Higher incentives also doubled the likelihood (9.2 percentage points) that agents made banners or leaflets to advertise the products, but the effect is not statistically significant (column 4). Finally, higher incentives did not increase the likelihood that agents hire an extra employee to help with the branchless banking activity, but they increased the likelihood that agents report making "other branchless banking investments." Overall, these results indicate that agents in the high × private treatment made more "business investments" than in the low × private treatment, although not on all dimensions. Differences

[20]Table A.9 studies the heterogeneous effect of our treatments on effort, by agent characteristics. Higher financial incentives are expected to have a larger impact on agents for whom these incentives are presumably more high-powered; namely, the poorest and least prosocially motivated. The results in Table A.9 show that it is indeed the case that the increase in agents' effort is stronger among the poorest (columns 1-3) and the least prosocially motivated agents (columns 4-6). Accordingly, the take-up of the new financial products increases only for these agents (columns 1 and 4).

[21]We measure task allocation with a dummy variable that equals one if the agent answers "yes" to the question on whether she "dedicated time to a specific activity." The binary response was designed to minimize reporting errors.

between the high × public treatment and the low × public treatment go in a similar direction but are slightly smaller in magnitude and less precisely estimated.

We have shown that higher incentives prompt agents to provide more effort towards promoting the products and increasing take-up. One possibility is that this comes together with a change in agents' targeting. Higher incentives may, for example, incentivize agents to target wealthier and more financially literate households, who have a higher propensity to adopt the products but who may benefit less from their adoption. We test this possibility by estimating an interacted version of Equation 1, where we interact the treatments with a dummy for whether the household is wealthy (i.e., wealth score above the median) or financially literate (i.e., scored above the median on a financial literacy test). Table A.12 columns 2-3 and 5-6 show that higher incentives do not affect agents' targeting: agents are equally likely to target wealthy/literate vs. non-wealthy/illiterate households in the high vs. low incentives treatment, and this is true both in the public and private treatment (see the three p-values at the bottom of the table).[22] Hence, we observe no differences across treatments in the extent to which the poor/financially illiterate households take up the products relative to the wealthier/illiterate households (columns 1 and 4).

In sum, agents respond strongly to higher incentive levels but respond less strongly to the transparency of these incentives. The latter result may be explained by the fact that the agents were not explicitly informed by us about the transparency of their incentives and may have only partially learned about it from other villagers. Alternatively, agents may simply not have fully anticipated the extent of the signaling effect.

[22] For ease of exposition, Table A.12 presents (i) the difference-in-difference coefficient *(High - Low)* × *(Private-Public)* for wealthy/financially literate households in Panel A, (ii) the corresponding coefficient for non-wealthy/financially illiterate households in Panel B, (iii) the p-value for the difference in these two coefficients ("p-value Panel A=Panel B") at the bottom of the table, estimated with the triple interaction term from the fully interacted model.

5.2 Potential Clients' Perceptions and Trust

In the previous section, we showed that higher financial incentives increase agent effort. When information about incentives is private, we observe that this increased effort leads to greater take-up and usage of the new financial products (Section 4). When, however, this information is public, agents' increased effort does *not* translate into higher take-up or usage. In this section, we show that this occurs due to a negative (positive) signal conveyed by high (resp., low) incentives, which leads to lower (resp., higher) levels of trust in the new financial products and their providers, and negatively (resp., positively) affects their demand.

In our endline survey, we collected comprehensive data on household respondents' perceptions of several attributes associated with the branchless banking products, the agent herself, and the bank, which we use to test the signaling effect of financial incentives. Specifically, we asked four different questions about respondents' level of trust in the product (i.e., how reliable and safe they think the product is), three questions about their level of trust in the bank and the banking system more generally, and four questions about the agent's quality and trustworthiness.[23] In the main analysis, we create four principal components that capture variation from questions on perceptions about the product ("trust in product"), the bank ("trust in bank"), the agent ("trust in agent"), and all perceptions combined ("trust all"). For ease of interpretation, we normalize each principal component on a scale of 0 to 1.

We start by looking at the raw data in Figure A.6, using the principal component that

[23] Questions about trust in the products: *(i) On a scale of 1 to 10, what is your perception of how reliable the bank's products are?; (ii) On a scale of 1 to 5, do you agree with the following statement? The fees/costs of the bank's products are reasonable; (iii) On a scale of 1 to 5, do you agree with the following statement? No one can steal my money from the products offered by the bank; (iv) On a scale of 1 to 10, what is your perception of how safe the bank's products are?* Questions about trust in the bank: *(i) On a scale of 1 to 5, how much confidence do you have in the enforcement of contracts between the bank and their customers?, (ii) On a scale of 1 to 5, do you agree that people in your village do not typically trust the local bank?, and (iii) On a scale of 1 to 5, how much confidence do you have in the enforcement of contracts between state-owned banks and their customers?* Questions about trust in the agent: *(i) On a scale of 1 to 5, how likely is it that a person goes to the agent to withdraw 500,000 IDR from their own account and the agent does not give them all the money back? (ii) On a scale 1 to 10, how competent do you think the agent is at doing his/her branchless banking job? (iii) On a scale of 1 to 10, do you think the agent would be willing to do something that earns him/her money but hurts the community?, and (iv) If you dropped your wallet with 100,000 IDR in it and the agent found it, what do you think is the likelihood that he/she will give it back to you?*

combines all questions about trust (product, agent, and bank), see also Panel D in Table A.3. In villages where incentives are high (pink bars), we find that respondents who learn about the commissions (public treatment) are less likely to trust the product and its providers than those who are not given this information (private treatment), although the difference is not significant at conventional levels (p-value of 0.132). The opposite is true in villages where incentives are low (grey bars): respondents in the public treatment are *more* likely to trust the product and its providers than in the private treatment (p-value of 0.014). The magnitude of this effect corresponds to 0.46 standard deviations of the first principal component of all of our trust variables. This provides suggestive evidence that, in the absence of any information (i.e., in the private treatment), potential clients likely perceive agents' incentives to be somewhere between the low and high levels. Accordingly, providing information about low incentives to prospective clients increases trust. On the contrary, information about high incentives reduces trust.[24] Interestingly, Figure A.6 suggests that an organization that aims to maximize trust should purposely pay low incentives to its employees and make this information public.

In Table 3, we present the corresponding results using Equation 1, and analyze trust in the products, the bank, and the agent separately. We also assess the effect of our treatments on respondents' perceptions of agent earnings, which is the only information about the product or the agent that was differently revealed to respondents across treatments.

Column 1 of Table 3 shows that in the high incentives treatment, household respondents are 5 percentage points (8.4%) more likely to perceive agents' earnings as being "fair or generous," as opposed to "too low." This effect is only present in the public incentives treatment (see coefficient for *(High - Low)* $\times$ *Public*). The effect is driven both by more people in the high $\times$ public treatment believing that the compensation is fair or generous and more people in

[24] Recall that agents' effort response to higher incentives does not substantially differ in the private and public treatment. This implies that the effects observed on clients' perceptions are likely explained by the signal conveyed by the incentives, rather than by any actions taken by the agent in response to the public information.

the low × public treatment believing that the incentives are too low. Interestingly, Table A.13 column 1 shows that a large fraction of households (46%) believe that agent's pay is commission-based and this fraction does not differ with the level of the public incentives. Recall from Section 2.2 that all respondents were informed about the identity of the agent and the account's conditions (fees, deposit, interest rates). Perceptions of these variables should not vary across treatments by construction.

When incentives are private, perceived agents' earnings do not vary with the actual incentives paid (see coefficient for *(High - Low)* × *Private*). This result confirms that, in our setting, information about agent earnings does not diffuse in the village unless households are explicitly informed about it.

In columns 2-4 of Table 3 we show that, when incentives are public, higher levels elicit lower trust in the product, in the bank, and in the agent (see coefficient for *(High - Low)* × *Public*). This effect is driven both by people in the low × public treatment having *higher* levels of trust in the product and its providers than in the private treatment, and by people in the high × public treatment having *lower* trust than in the private treatment. When private, higher incentives instead do not affect trust, as expected.

The coefficient for *(High - Low)* × *(Public - Private)* in Table 3 isolates the signaling effect of higher public financial incentives on potential clients' perceptions. We find a strong negative and significant effect. This effect is similar across each of the three principal components, suggesting that potential clients' perceptions about the products, the bank, and the agent are all equally impacted by the new information about the agent's compensation. Because trust in the product, the bank, and the agent all positively correlate with take-up (as seen in Panel B of Figure A.5), we cannot pin down precisely which of the dimensions of trust matter more in our context.

Table A.13 examines each individual perception question separately and shows that both the product's perceived reliability and its safety decline with higher public incentives (columns 2 and 5, respectively). High $\times$ public incentives also reduce trust in contract enforcement in general and thus trust in the overall banking system (column 8). Finally, the perceived trustworthiness, competence, and pro-sociality of the agent all go down with higher public incentives (columns 9-12). The reverse is true for the low $\times$ public treatment, where we see increases in these variables.

Next, we explore the heterogeneous effect of our treatments on perceptions by client characteristics. Table 4 shows that the negative effect of publicizing high incentives on client perceptions is concentrated among potential clients who have *little* information and *low* trust about the agent and the products at baseline, i.e., those who report not knowing or not trusting the agent at baseline (columns 1 and 4), and those who report not knowing what branchless banking is at baseline (column 7). The effects are instead small and non-significant for more informed people, and for those who know the product and the agent at baseline.[25] These results are consistent with a signaling story: perceptions vary only for individuals who are uninformed at baseline and who need to rely on external signals to form their opinions about trust. The results are instead inconsistent with any other story that does not predict perceptions to change more for uninformed individuals.[26]

In sum, informing potential clients about the agent's high (resp., low) incentives reduces (resp., increases) their levels of trust in the bank, the agent, and the product, in turn reducing (resp., boosting) their demand. These effects are stronger among customers who have less information about the agent and the product, and who update their perceptions to a greater degree. These findings echo those from settings where either high prices or high wages are used as signals of the quality of the product (Milgrom and Roberts, 1986; Benabou and

[25] Table 4 (columns 2-3, 5-6, 8-9) shows that there is no difference across treatments in the extent to which agents target their effort towards "more-knowledgeable" vs. "less-knowledgeable" respondents. Differences in demand perceptions are thus unlikely driven by differential agent targeting.

[26] For example, the high $\times$ public treatment could adversely affect perceptions by making pay inequality in the community more salient, but if that were the case, the effect should also exist among informed individuals.

Tirole, 2003). Likewise, they align with recent literature documenting how people rely on seemingly innocuous observable cues to make consequential economic decisions (Granzier, Pons, and Tricaud, 2019; Macchi, 2020).

6 Long-Term Effects and Optimal Policy Choices

6.1 Long-Term Effects and Persistence

We have so far discussed the effect of our treatments at endline, 14-21 months after the introduction of branchless banking. The goal of this section is twofold: (i) assess whether take-up of the banking products increased over time; and (ii) assess whether the treatment effects on take-up persist over time after the endline survey. To do so, we leverage bank's administrative data available for the period January-October 2021, 38 to 50 months after the start of the intervention. These "long-term" data are available at the village level and contain information on (i) the number of adopters of the saving account or the digital wallet in the village in each given month (take-up), (ii) the total number of transactions performed by all clients in the village per month, (iii) the total account balance in the village per month, (iv) the total volume of payments performed through the bank in the village every month. To avoid any seasonal effects, we use the median take-up and usage across the ten months for which we have available long-term data as our main outcome variables. Because the long-term data are not restricted to entrepreneurs but are representative of the whole population, we "re-scale" them to be representative of entrepreneurs only for comparability with the short-term data.[27] With this re-scaling procedure, average take-up and usage are comparable in the long and short-term data.[28]

[27] We do so by dividing long-term take-up and usage by $(\alpha + \gamma * (1 - \alpha))$, where α is the share of villagers who are entrepreneurs (12.6%, on average, obtained from our household listing) and γ is the ratio between the take-up rate of non-entrepreneurs and the take-up rate of entrepreneurs (0.3, obtained from a consumer survey we conducted as part of a separate study).

[28] Recall that we survey a random 12 respondents per village in our short-term endline data. As a result, averaging that data at the village level is equivalent to averaging it at the household level.

Figure A.7 presents descriptive statistics on long-term take-up by treatment. Two points are of note. First, in all treatments, take-up nearly triples in the long term relative to the short term. In the high $\times$ private treatment, for example, take-up increases from 2.7% in the short term (first bar of Figure A.3) to 7.4% in the long term (first bar of Figure A.7). Take-up increases similarly in all other treatments. If we aggregate take-up across all treatments, we estimate that the take-up rate in the long term is 3.6% vs. 1.3% in the short term. These data are consistent with branchless banking taking time to be adopted in the community. Second, differences in take-up across treatments are all magnified in absolute values in the long term relative to the short term, although these differences lose precision due to the lower sample size (observations are now at the village level).[29]

Table 5 presents the long-term results on take-up and usage using Equation 1. Column 1 shows similar results on take-up to those in Figure A.7. Columns 2-7 show that higher private incentives increase the frequency of transactions by 632% (413%, in per-client terms, though not significant), the account balance by 68% (no effect in per-client terms), and the volume of payment by 179% (210% in per client terms). The fact that the per-client account activity increases over time indicates that the account dormancy rate is limited in our context. As with the short-term data, higher public incentives do not increase adoption.[30]

To sum up, this section has shown that take-up and adoption increased over time and that the results we documented in the short term are magnified two years later. This indicates that fostering trust in the agents and the products when products are initially introduced contributes to increasing long-term adoption and usage.

[29]Figure A.7 re-scales the long-term data assuming that $\gamma = 0.3$ (see footnote 27). Table A.14 presents the robustness of the results to using different values of γ (from 0.5 to 0.1).

[30]Table 5 presents the results using the same rescaling procedure as in Figure A.3 (scaling up numbers to be representative of entrepreneurs only). For completeness, Table A.15 presents the results without any scaling up (representative of the whole population).

6.2 Discussion: Optimal Policy Choices

This section aims to assess which incentives' level and pay transparency policy maximize banks profits, customers' welfare, and agents' welfare.

We estimate that the bank maximizes its profits in the high × private treatment. In our setting, the bank aims to maximize (i) clients' account balance (to generate profits on the spreads), and (ii) the fees earned from clients' transactions (to cover operational costs). Recall that each time a client withdraws money from her account, she pays 3,000 IRP, of which 2,000 IRP goes to the bank and the rest to the agent. The client pays no fee for depositing money or opening an account. To recover the incentive of 2,000 IRP (resp., 10,000 IRP) paid to the agent per new customer in the low (high) incentives treatment, the bank needs each client to withdraw at least once (resp., five) times. Using the long-run bank administrative data, we calculate that the bank recovers the cost of the incentives payout in less than three months in all treatments. The net revenues earned by the bank per village and per year is 819,000 IRP when incentives are high and private, 553,000 IRP when incentives are high and public, 131,000 IRP when incentives are low and private, and 512,000 IRP when incentives are low and public.[31] Imagine first that the bank has control over the level of the incentives but no control over the transparency of the incentives (e.g., because the norm is to reveal or not to reveal the incentives and the bank cannot deviate from this norm). In environments where pay is private, the bank should optimally choose high incentives, while it should choose low incentives if the pay is public. Imagine now that the bank can influence pay transparency in the community but has no control over the level of the incentives. Our results indicate that the bank should hide information about the level of the incentives if the latter are high and, instead, publicize them to potential clients if incentives are low. Finally, if the bank can control both the level and the transparency of incentives, the bank should opt for high

[31] These are calculated as (the average total number of transactions per agent per month)×12×2,000 number of clients×commission. This equals 6.4×12×2,000-11.3×2,000 = 131,000 in the low × private treatment, 23.5×12×2,000-5.6×2,000 = 512,000 in the low × public treatment, 28.1×12×2,000-16.2×10,000 = 553,000 in the high × public treatment, 41.8×12×2,000-18.4×10,000 = 819k in the high × private treatment.

$\times$ private incentives.

We estimate that the high $\times$ private treatment also likely maximizes customer welfare. As branchless banking has been shown to be at least weakly welfare-improving (see the discussion in the Introduction), the best treatment from the customers' point-of-view is the one that maximizes branchless banking products' take-up and usage, i.e., the high $\times$ private treatment. Note that this result holds only for products that are at least weakly beneficial, which is not necessarily the case for all financial products.

From the point of view of the agents, our results are more nuanced. The low $\times$ public treatment dominates the low $\times$ private one as it leads to higher take-up (and thus more earnings) with a similarly low level of effort. It also dominates the high $\times$ public treatment because it leads to the same take-up (same earnings) for a lower cost of effort. What is unclear is whether the low $\times$ public treatment dominates the high $\times$ private one as the former leads to low take-up with low effort while the latter leads to high take-up with high effort. Which of the two dominates will depend on the number of transactions a given client performs after signing up and on the cost of effort. The high $\times$ private treatment will dominate the low $\times$ public one if the number of transactions per client is high enough relative to the cost of effort.

7 Conclusions

In partnership with a large bank in Indonesia, we designed an experiment that creates exogenous variation in both the *level* and the *transparency* of financial incentives paid to branchless banking agents for acquiring new clients. We show that raising these incentives has diverging effects on take-up and usage depending on whether or not this information is disclosed to potential clients. When the level of the incentives is *not* disclosed, increasing them is shown to boost the take-up and the usage of the financial products. Yet, when the level is disclosed, the effect of higher incentives is muted. We show that this is because potential clients who learn that the agent is paid a high incentive have a lower perception of the quality and trustworthiness of the product, the agent, and the bank, thus reducing the products' demand. In contrast, those who learn that the agent is paid a low incentive have a higher perception of the trustworthiness of the product and its providers.

Our results reinforce previous evidence in the literature on the effectiveness of financial incentives in increasing the effort exerted by local delivery agents (e.g., Aubert, de Janvry, and Sadoulet 2009; Giné, Mansuri, and Shrestha 2020). Crucially, however, we argue that in contexts where information and experience about a product are limited and trust is low, public information about financial incentives provides a meaningful signal about the quality and trustworthiness of the product and its providers. In our setting, the positive effects of higher agent incentives on take-up only materialize if these incentives are kept private. When incentives are public information, raising their level does not increase take-up, thus wasting the organization's resources, as well as agents' time and energy in promoting the products.

Our findings also reinforce recent evidence highlighting the importance of trust in the financial sector when attempting to increase financial inclusion (Breza, Kanz, and Klapper, 2020; Bachas et al., 2021). From a policy standpoint, organizations promoting financial products need to carefully consider the signals they send to potential clients, as these can shape the demand for their products. Specific attention should be paid to the transparency of financial incentives along with their level. If (as in our context) high (low) financial incentives convey a negative (positive) signal about the product or its providers, organizations seeking to maximize take-up would be better off raising the incentive level without, however, disclosing this information to the community. If an organization aims to maximize trust (instead of take-up), it may purposely pay low incentives to its employees and make this information public.

The finding that organizations may benefit from keeping the level of agents' incentives private information and that this may improve aggregate welfare – e.g., by improving financial inclusion – contrasts with the common perception that transparency unambiguously improves welfare and that consumer protection regulations should enforce full transparency. This is not to say that consumers are necessarily always better off when they are less informed. For example, a recent multi-country mystery shopper audit (Ghana, Mexico, and Peru) that sent actors posing as customers to multiple financial institutions seeking credit and savings products, finds that potential customers are rarely offered the highest-yielding product because the bank staff is incentivized to sell more profitable products (Giné and Mazer, 2022). Disclosing the level of the incentives agents earn for each product would potentially attenuate such misbehavior. Similarly, disclosing the incentives paid to pharmaceutical promoters or doctors is necessary from an ethical standpoint and helps prevent devious behaviors. The question that naturally arises in these contexts is how to balance the objectives of consumer protection and the socially desirable objective of increasing the take up of beneficial technologies. Further research is needed to get a better grasp of these trade-offs.

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Table 1: Take-up and Usage

	(1)	(2)	(3)	(4)
	Take-up	Transactions Amount (IHS)	Balance (IHS)	Saving (IHS)
(High - Low) $\times$ Private	0.021***	0.184**	0.196**	0.191**
	(0.008)	(0.078)	(0.078)	(0.078)
(High - Low) $\times$ Public	0.003	0.036	0.003	0.001
	(0.004)	(0.023)	(0.027)	(0.025)
(High - Low) $\times$ (Public - Private)	-0.018^{**}	-0.148^{*}	-0.193^{**}	-0.190^{**}
	(0.009)	(0.081)	(0.082)	(0.081)
Regression Coefficients				
High $\times$ Private	0.021***	0.184**	0.196**	0.191**
	(0.008)	(0.078)	(0.078)	(0.078)
High $\times$ Public	0.006	0.049**	0.039*	0.029
	(0.005)	(0.022)	(0.020)	(0.024)
Low $\times$ Public	0.002	0.013	0.036*	0.029
	(0.004)	(0.010)	(0.019)	(0.022)
Observations	4644	4828	4828	4613
R-squared	0.006	0.008	0.007	0.007
Mean Dep. Var.	0.013	0.046	0.055	0.060
Mean Dep. Var. for Low $\times$ Private	0.006	0.000	0.000	0.014
p-value High $\times$ Private - High $\times$ Public	0.048	0.094	0.049	0.041
p-value High $\times$ Private - Low $\times$ Public	0.016	0.029	0.045	0.041

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. Columns 2-4 are expressed in IDR and are transformed using an inverse hyperbolic sine (IHS) transformation. Dependent variables in columns 1 and 4 come from the survey data. Dependent variables in columns 2-3 come from the bank recorded data. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 2: Agent Effort

	(1)	(2)	(3)	(4)	(5)	(6)
	Agent Effort			Agent Sales Strategy		
	Number of Times Products are Advertised	Learned about Products from Agent	Agent Effort (PC)	Products Offered by Agent	Agent Pro-Actively Promoted Products	Agent Sales Strategy (PC)
(High - Low) × Private	0.203**	0.015*	0.006**	0.038***	0.033***	0.035***
	(0.083)	(0.008)	(0.003)	(0.010)	(0.010)	(0.010)
(High - Low) × Public	0.129***	0.015***	0.005***	0.025***	0.018***	0.022***
	(0.028)	(0.004)	(0.001)	(0.007)	(0.006)	(0.006)
(High - Low) × (Public - Private)	-0.074	-0.000	-0.001	-0.013	-0.015	-0.014
	(0.089)	(0.009)	(0.003)	(0.012)	(0.011)	(0.012)
Regression Coefficients						
High × Private	0.203**	0.015*	0.006**	0.038***	0.033***	0.035***
	(0.083)	(0.008)	(0.003)	(0.010)	(0.010)	(0.010)
High × Public	0.130***	0.005	0.003***	0.034***	0.028***	0.031***
	(0.033)	(0.005)	(0.001)	(0.007)	(0.006)	(0.007)
Low × Public	0.001	−0.010**	−0.002**	0.009	0.010*	0.009*
	(0.022)	(0.004)	(0.001)	(0.006)	(0.006)	(0.006)
Observations	4638	4639	4638	4639	4639	4639
R-squared	0.008	0.009	0.011	0.009	0.008	0.008
Mean Dep. Var.	0.130	0.013	0.004	0.033	0.031	0.032
Mean Dep. Var. for Low × Private	0.057	0.013	0.003	0.014	0.014	0.014
p-value High × Private - High × Public	0.390	0.203	0.245	0.706	0.625	0.663
p-value High × Private - Low × Public	0.011	0.001	0.001	0.005	0.015	0.008

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. Columns 3 and 6 compute the first principal component from the variables in columns 1-2 and 4-5, respectively. ***p<0.01, **p<0.05, *p<0.1

Table 3: Perceptions of Potential Clients

	(1)	(2)	(3)	(4)	(5)
	Perceived Agent Earnings	Trust in Product (PC)	Trust in Bank (PC)	Trust in Agent (PC)	Trust All (PC)
(High - Low) × Private	-0.030	0.009	-0.006	0.003	0.004
	(0.028)	(0.010)	(0.014)	(0.011)	(0.009)
(High - Low) × Public	0.049^{***}	-0.018^{**}	-0.024^{**}	-0.019^{***}	-0.021^{***}
	(0.018)	(0.007)	(0.010)	(0.007)	(0.006)
(High - Low) × (Public - Private)	0.078^{**}	-0.026^{**}	-0.018	-0.021	-0.024^{**}
	(0.033)	(0.013)	(0.017)	(0.013)	(0.011)
Regression Coefficients					
High × Private	-0.030	0.009	-0.006	0.003	0.004
	(0.028)	(0.010)	(0.014)	(0.011)	(0.009)
High × Public	0.017	0.003	-0.004	-0.006	-0.001
	(0.022)	(0.009)	(0.012)	(0.009)	(0.008)
Low × Public	-0.032	0.020^{**}	0.020	0.013	0.019^{**}
	(0.021)	(0.009)	(0.012)	(0.009)	(0.008)
Observations	4606	4636	4636	4638	4638
R-squared	0.004	0.010	0.024	0.005	0.018
Mean Dep. Var.	0.574	0.504	0.767	0.708	0.591
Mean Dep. Var. for Low × Private	0.580	0.496	0.765	0.705	0.585
p-value High × Private - High × Public	0.071	0.478	0.896	0.354	0.488
p-value High × Private - Low × Public	0.930	0.189	0.049	0.298	0.039

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. We asked each respondent whether they perceived agent's commission to be fair, generous or too low. "Perceived Agent Earnings" is an indicator taking the value of one if the respondent thinks that the agent's commission is "fair or generous", as opposed to "too little." "Trust in Product (PC)," "Trust in Bank (PC)," "Trust in Agent (PC)," and "Trust All (PC)" compute the first principal component from the variables in columns 2-5, 6-8, 9-12, and 2-12 of Table A.13, respectively. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Heterogeneous Effects on Perceptions of Potential Clients and Agent Effort by Trust and Knowledge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Trust All (PC)	Agent Effort (PC)	Agent Sales Strategy (PC)	Trust All (PC)	Agent Effort (PC)	Agent Sales Strategy (PC)	Trust All (PC)	Agent Effort (PC)	Agent Sales Strategy (PC)
Panel A Sample:	Friends or Family of the Agent			Trust the Agent's Financial Advices			Know Branchless Banking		
(High - Low) × (Public - Private)	0.001	0.003	-0.012	-0.006	-0.015	0.052	-0.013	-0.020	-0.089
	(0.019)	(0.004)	(0.030)	(0.038)	(0.018)	(0.046)	(0.036)	(0.023)	(0.057)
Panel B Sample:	Not Friends or Family of the Agent			Do Not Trust the Agent's Financial Advices			Do Not Know Branchless Banking		
(High - Low) × (Public - Private)	-0.033^{***}	-0.003	-0.014	-0.025^{**}	0.001	-0.019	-0.025^{**}	0.001	-0.008
	(0.012)	(0.004)	(0.012)	(0.011)	(0.002)	(0.012)	(0.011)	(0.002)	(0.011)
Observations	4638	4638	4639	4638	4638	4639	4638	4638	4639
% Observations in Panel A	25.61	25.64	25.63	8.41	8.41	8.41	8.09	8.09	8.08
R-squared	0.941	0.037	0.052	0.941	0.053	0.050	0.940	0.051	0.051
Mean Dep. Var.	0.591	0.004	0.032	0.591	0.004	0.032	0.591	0.004	0.032
Mean Dep. Var. for Low × Private	0.585	0.003	0.014	0.585	0.003	0.014	0.585	0.003	0.014
p-value Panel A=Panel B	0.117	0.240	0.965	0.629	0.371	0.134	0.741	0.386	0.150

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. "Agent Effort (PC)" and "Agent Sales Strategy (PC)" compute the first principal component from the variables in columns 1-2 and 4-5 of Table 2, respectively. "Trust All (PC)" computes the first principal component from the variables in columns 2-12 of Table A.13. In columns 1-3, Panel A [resp., B] restricts the observations to households in villages where the respondent knows the agent at baseline [resp., does not know the agent)]. Columns 4-6 and 7-9 are similarly divided relative to whether the respondent trusts the financial advice given by the agent at baseline and whether the respondent knows about branchless banking at baseline, respectively. "p-value Panel A = Panel B" presents the p-value from the equality of the coefficients (High - Low) × (Public - Private) in Panel A and B using the fully interacted model. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Long-Term Effects on Take-Up and Usage (Re-scaled)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Take-Up Rate	Transaction Frequency	Transaction Frequency/Number of Clients	Balance (IHS)	Balance/Number of Clients (IHS)	Payments (IHS)	Payments/Number of Clients (IHS)
(High - Low) × Private	0.045**	100.781***	13.556	1.095*	-0.003	2.955***	1.320**
	(0.020)	(33.578)	(9.734)	(0.599)	(0.263)	(0.979)	(0.535)
(High - Low) × Public	-0.001	12.460	0.553	-0.165	0.008	-0.196	0.060
	(0.015)	(29.800)	(2.248)	(0.431)	(0.198)	(0.654)	(0.306)
(High - Low) × (Public - Private)	−0.046*	−88.321**	-13.003	−1.260*	0.011	−3.151***	−1.260**
	(0.025)	(44.613)	(10.567)	(0.735)	(0.332)	(1.167)	(0.611)
Regression Coefficients							
High × Private	0.045**	100.781***	13.556	1.095*	-0.003	2.955***	1.320**
	(0.020)	(33.578)	(9.734)	(0.599)	(0.263)	(0.979)	(0.535)
High × Public	0.024**	60.018**	-0.571	0.629	-0.103	1.412**	0.393
	(0.012)	(27.265)	(2.901)	(0.445)	(0.246)	(0.611)	(0.309)
Low × Public	0.025**	47.558***	-1.124	0.794*	-0.111	1.608**	0.333
	(0.012)	(16.355)	(2.565)	(0.460)	(0.246)	(0.640)	(0.309)
Observations	401	401	401	401	401	401	401
R-squared	0.051	0.041	0.116	0.037	0.016	0.075	0.061
Mean Dep. Var.	0.036	66.668	5.912	2.243	0.523	3.095	1.074
Mean Dep. Var. for Low × Private	0.013	15.939	3.278	1.612	0.588	1.643	0.629
p-value High × Private - High × Public	0.338	0.328	0.200	0.419	0.666	0.114	0.084
p-value High × Private - Low × Public	0.374	0.137	0.157	0.612	0.636	0.181	0.068

Notes: Observations are the village level. Each observation corresponds to the village-level median of monthly data between January and October 2021. All regressions control for stratification variables. Robust standard errors in parenthesis. Take-up is computed as the number of clients divided by the population (from our village survey). Columns 4 to 7 are transformed using an inverse hyperbolic sine (IHS) transformation. We re-scaled the data to be comparable to the short-term sample of entrepreneurs. To do this, we compute take-up for entrepreneurs as the village-level take-up rate divided by $(\alpha + \gamma * (1 - \alpha))$, where α is the share of villagers who are entrepreneurs and γ is equal to 0.3. ***p<0.01, **p<0.05, *p<0.1.

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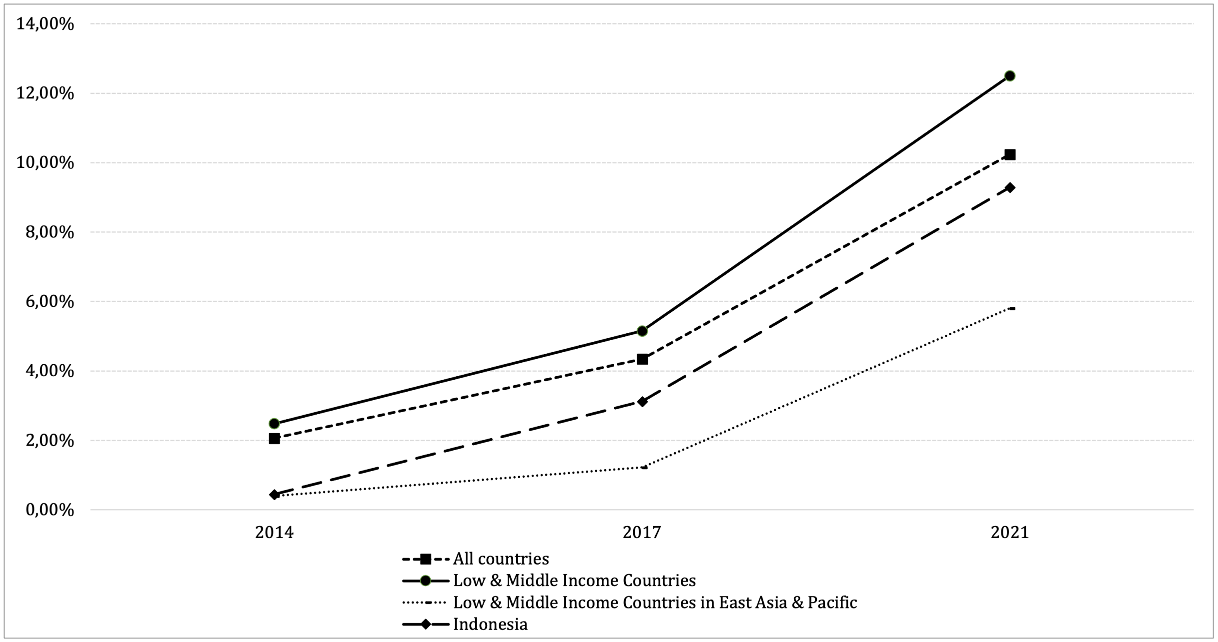
Appendix Figures and Tables

Figure A.1: Evolution of Take-up of Mobile Money Products Around the World

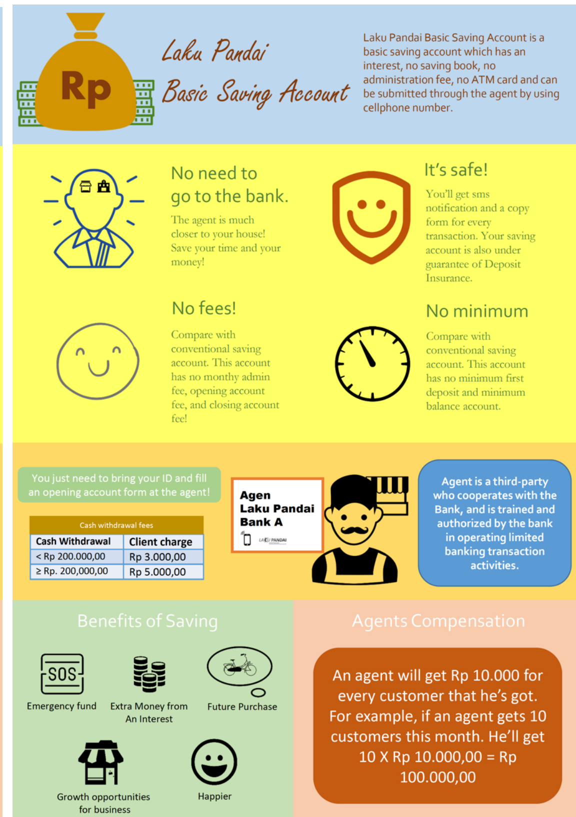


Notes: This figure presents data from the Global Findex Dataset on the percentage of respondents 15 years or older who report having personally used a mobile money service in the past year.

Figure A.2: Leaflets

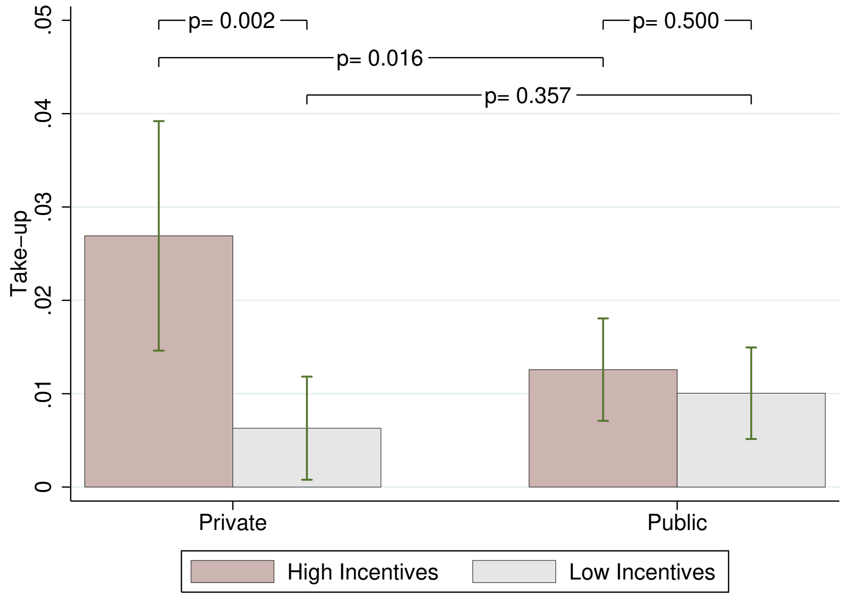
(a) Private Incentives

(b) Public & Low Incentives



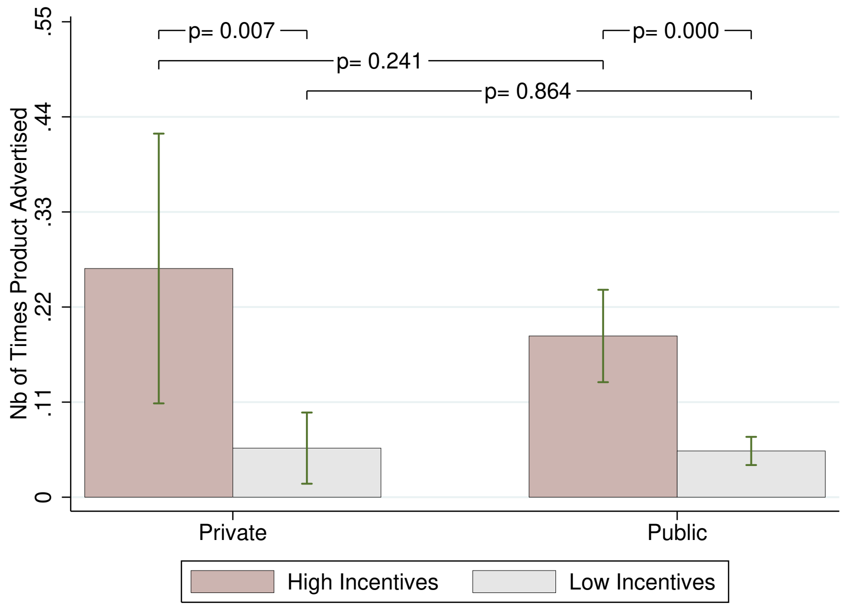
(c) Public & High Incentives

Figure A.3: Take-up of the Bank's Branchless Banking Products



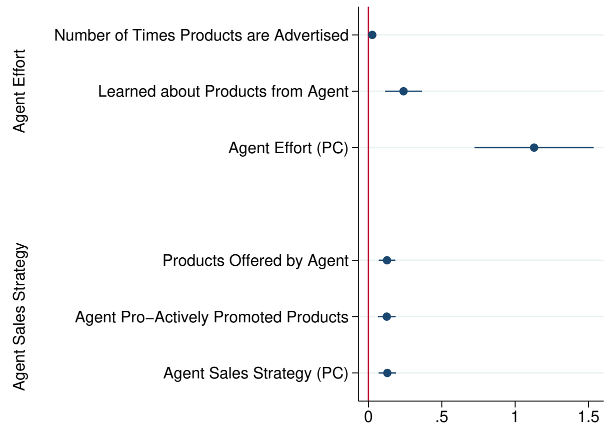
Notes: This figure presents the means and 95 percent confidence intervals of the take-up rate by treatment group. The two bars on the left (right) display the means when incentives are private (public). The top horizontal bars show p-values for t-tests of equality of means between different treatment groups.

Figure A.4: Agent Effort

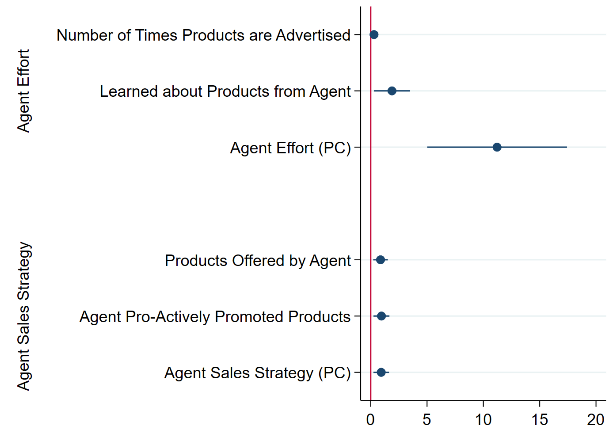


Notes: This figure presents the means and 95 percent confidence intervals of the number of times the agent advertised the product to the household by treatment group. The two bars on the left (right) display the means when incentives are private (public). The top horizontal bars show p-values for t-tests of equality of means between different treatment groups.

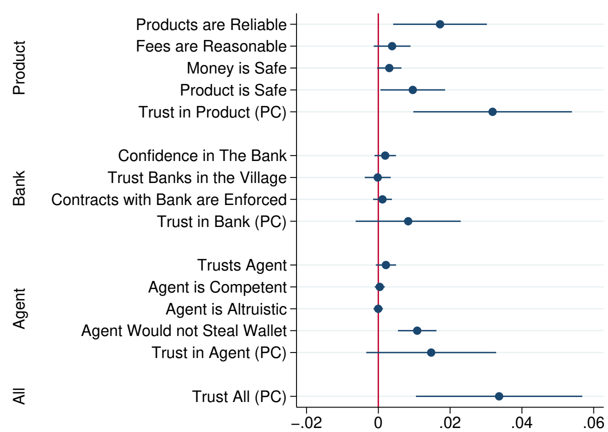
Figure A.5: Correlation of Take-up and Transaction Amount (IHS) with Agent Effort and Perceptions of Potential Clients



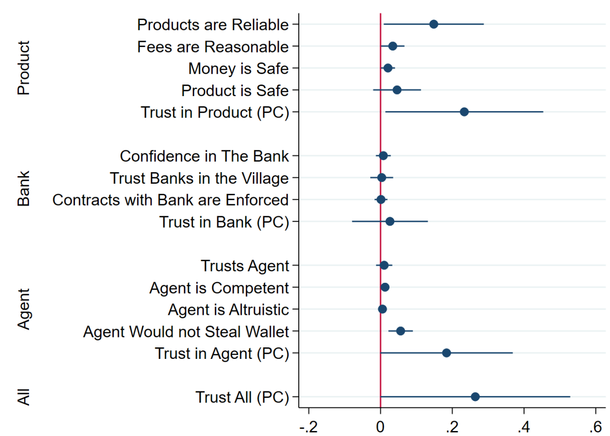
(a) Take-up and Agent Effort



(b) Take-up and Perceptions



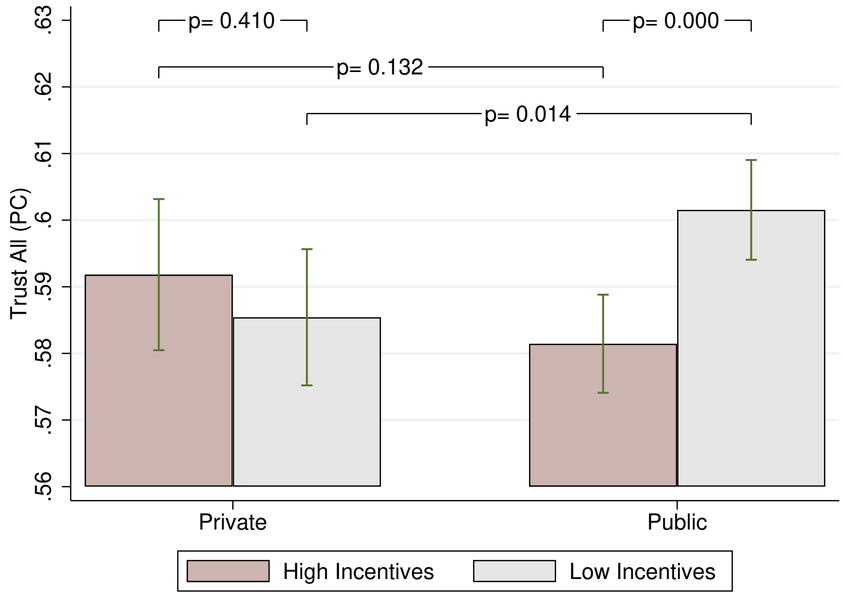
(c) Transaction Amount (IHS) and Agent Effort



(d) Transaction Amount (IHS) and Perceptions

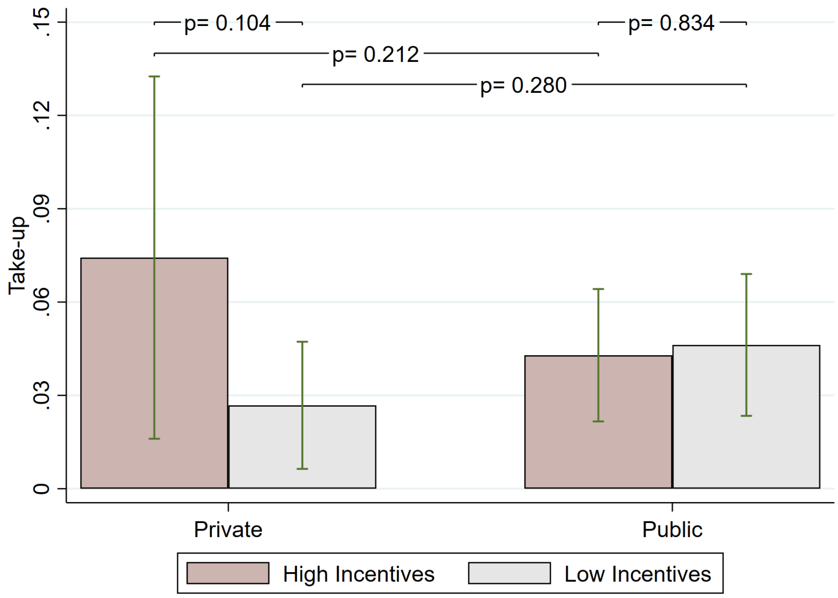
Notes: This figure presents the correlation between take-up and agent effort/agent sales strategy in Panel (a), the correlation between take-up and client perceptions in Panel (b), the correlation between balance (IHS) and agent effort/agent sales strategy in Panel (c), the correlation between balance (IHS) and client perceptions in Panel (d), controlling for stratification variables and with standard errors clustered at the agent level.

Figure A.6: Trust in Product, Agent, and the Bank



Notes: This figure presents the means and 95 percent confidence intervals of trust in the products, agent, and bank (principal component of 4 product trust questions, 4 agent trust questions, 3 bank trust questions). The two bars on the left (right) display the means when incentives are private (public). The top horizontal bars show p-values for t-tests of equality of means between different treatment groups.

Figure A.7: Take-up of the Bank's Branchless Banking Products - Long Term Effects



Notes: This figure presents the means and 95 percent confidence intervals of the take-up rate in the long term (38 to 50 months after the start of the intervention). One observation per village. The two bars on the left (right) display the means when incentives are private (public). The top horizontal bars show p-values for t-tests of equality of means between different treatment groups. The long-term results are computed by scaling up numbers to be representative of entrepreneurs only with $\gamma = 0.3$ (see footnote 31). The four bars on the left (right) display the means when incentives are private

Table A.1: Summary Statistics and Balance Checks

	(1) Obs.	(2) Mean	(3) Std. Dev.	(4) p-value F-stat Joint	(5) p-value (High-Low)× Private	(6) p-value (High-Low)× Public	(7) p-value (Public-Private)× High	(8) p-value (Public-Private)× Low
Panel A: Village Characteristics								
Village Size	401	964.5	592.2	0.252	0.424	0.084*	0.974	0.543
Distance to Nearest Bank Branch (in km)	401	12.32	6.944	0.951	0.890	0.862	0.692	0.706
Internet Coverage	401	0.673	0.470	0.519	0.606	0.367	0.172	0.832
Panel B: Agent Characteristics								
Female	400	0.482	0.500	0.612	0.625	0.216	0.987	0.702
Highest Degree=Primary School	400	0.033	0.178	0.603	0.233	0.718	0.609	0.462
Highest Degree=High School	400	0.535	0.499	0.570	0.190	0.945	0.651	0.289
Highest Degree=Tertiary Education	400	0.433	0.496	0.798	0.383	0.955	0.808	0.394
Main Occupation=Non Farm Business	400	0.850	0.358	0.694	0.304	0.532	0.365	0.425
Main Occupation=Agriculture or Other	400	0.160	0.367	0.456	0.136	0.532	0.188	0.360
Volunteered in the Past Year	400	0.328	0.470	0.759	0.841	0.654	0.545	0.425
Has a Mobile Phone	400	1.000	0.000	.	.	.	.	.
Has a Laptop	400	0.537	0.499	0.363	0.492	0.642	0.092*	0.549
Panel C: Household Characteristics								
Female	4828	0.591	0.492	0.030	0.109	0.724	0.618	0.082*
Highest Degree=Primary School	4828	0.234	0.424	0.585	0.229	0.541	0.476	0.850
Highest Degree=High School	4828	0.633	0.482	0.511	0.214	0.679	0.271	0.926
Highest Degree=Tertiary Education	4828	0.117	0.321	0.987	0.730	0.905	0.826	0.788
Main Occupation=Non Farm Business	4825	0.951	0.215	0.286	0.974	0.836	0.129	0.228
Main Occupation=Agriculture or Other	4824	0.056	0.231	0.409	0.658	0.672	0.284	0.273
Volunteered in the Past Year	4824	0.160	0.367	0.307	0.809	0.099*	0.152	0.976
Has a Mobile Phone	4828	0.931	0.253	0.560	0.368	0.508	0.849	0.408
Has a Laptop	4822	0.266	0.442	0.807	0.581	0.813	0.889	0.335
Made a Bank Transaction in the Last Month	4826	0.434	0.496	0.465	0.131	0.650	0.494	0.476
Has a Bank Saving Account	4827	0.550	0.498	0.103	0.108	0.123	0.881	0.329
Trust in State Banks (1 to 5)	4828	3.923	1.251	0.790	0.973	0.310	0.681	0.699
Trust in Non State Banks (1 to 5)	4828	3.207	1.349	0.696	0.455	0.393	0.629	0.284
Knows about Branchless Banking	4827	0.079	0.270	0.097	0.069*	0.336	0.751	0.169
Knows the Agent	4828	0.595	0.491	0.121	0.261	0.033**	0.844	0.932
Friend or Family of the Agent	4828	0.257	0.437	0.415	0.200	0.337	0.400	0.993

Notes: Columns 1-3 state the number of observations, sample mean, and standard deviation of the village-level variables in Panel A, agent-level variables in Panel B, and household-level variables in Panel C, respectively. Columns 4-8 present p-values estimated from a regression of each variable on the four treatment dummies, controlling for the stratification variables, and with standard errors clustered at the agent level. Column 4 presents the p-value from the joint test of significance of the four treatments. Columns 5-8 present the p-value from pairwise treatment comparisons: High × Private vs. Low × Private in column 5, High × Public vs. Low × Public in column 6, High × Public vs. High × Private in column 7, and Low × Public vs. Low × Private in column 8. ***p<0.01, **p<0.05, *p<0.1

Table A.2: Summary Statistics by Treatment (Baseline)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High × Private			Low × Private			High × Public			Low × Public		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Panel A: Village Characteristics												
Village Size	57	811.7	404.7	68	957.9	614.8	139	932.3	558.7	137	1,063.9	663.5
Distance to Nearest Bank Branch (in km)	57	13.07	5.793	68	12.06	6.760	139	12.78	7.153	137	11.68	7.258
Internet Coverage	57	0.702	0.462	68	0.691	0.465	139	0.633	0.484	137	0.693	0.463
Panel B: Agent Characteristics												
Female	56	0.536	0.503	68	0.471	0.503	139	0.518	0.501	137	0.431	0.497
Highest Degree=Primary School	56	0.054	0.227	68	0.015	0.121	139	0.036	0.187	137	0.029	0.169
Highest Degree=High School	56	0.482	0.504	68	0.603	0.493	139	0.525	0.501	137	0.533	0.501
Highest Degree=Tertiary Education	56	0.464	0.503	68	0.382	0.490	139	0.439	0.498	137	0.438	0.498
Main Occupation=Non Farm Business	56	0.804	0.401	68	0.882	0.325	139	0.863	0.345	137	0.839	0.368
Main Occupation=Agriculture or Other	56	0.232	0.426	68	0.118	0.325	139	0.144	0.352	137	0.168	0.375
Volunteered in the Past Year	56	0.339	0.478	68	0.338	0.477	139	0.331	0.472	137	0.314	0.466
Has a Mobile Phone	56	1.000	0.000	68	1.000	0.000	139	1.000	0.000	137	1.000	0.000
Has a Laptop	56	0.429	0.499	68	0.500	0.504	139	0.583	0.495	137	0.555	0.499
Panel C: Household Characteristics												
Female	687	0.597	0.491	816	0.583	0.493	1,674	0.593	0.491	1,651	0.590	0.492
Highest Degree=Primary School	687	0.220	0.414	816	0.249	0.433	1,674	0.226	0.419	1,651	0.241	0.428
Highest Degree=High School	687	0.649	0.478	816	0.619	0.486	1,674	0.637	0.481	1,651	0.629	0.483
Highest Degree=Tertiary Education	687	0.125	0.331	816	0.114	0.318	1,674	0.117	0.322	1,651	0.114	0.318
Main Occupation=Non Farm Business	686	0.958	0.201	816	0.958	0.200	1,673	0.947	0.223	1,650	0.949	0.220
Main Occupation=Agriculture or Other	686	0.054	0.226	816	0.048	0.213	1,672	0.061	0.239	1,650	0.057	0.232
Volunteered in the Past Year	686	0.147	0.355	816	0.152	0.359	1,672	0.177	0.382	1,650	0.153	0.360
Has a Mobile Phone	687	0.932	0.253	816	0.920	0.271	1,674	0.936	0.245	1,651	0.931	0.254
Has a Laptop	686	0.270	0.444	816	0.279	0.449	1,672	0.266	0.442	1,648	0.258	0.438
Made a Bank Transaction in the Last Month	687	0.444	0.497	816	0.408	0.492	1,673	0.442	0.497	1,650	0.434	0.496
Has a Bank Saving Account	687	0.557	0.497	816	0.512	0.500	1,674	0.571	0.495	1,650	0.543	0.498
Trust in State Banks (1 to 5)	687	3.943	1.228	816	3.929	1.228	1,674	3.950	1.228	1,651	3.884	1.293
Trust in Non State Banks (1 to 5)	687	3.204	1.339	816	3.254	1.335	1,674	3.226	1.354	1,651	3.167	1.354
Knows about Branchless Banking	687	0.089	0.285	816	0.060	0.238	1,674	0.087	0.282	1,650	0.077	0.267
Knows the Agent	687	0.633	0.482	816	0.569	0.496	1,674	0.628	0.483	1,651	0.560	0.497
Friend or Family of the Agent	687	0.300	0.459	816	0.250	0.433	1,674	0.260	0.439	1,651	0.240	0.427

Notes: Each row states the number of observations, the sample mean, and the standard deviation in each treatment group for village-level variables in Panel A, agent-level variables in Panel B, and household-level variables in Panel C.

Table A.3: Summary Statistics of Main Outcome Variables by Treatment (Endline)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High × Private			Low × Private			High × Public			Low × Public		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Panel A: Village Level Adoption												
Number of People in the Village who Take-Up	57	22.419	47.533	68	7.671	35.934	139	9.916	31.061	137	11.072	39.172
Panel B: Take-up and Usage												
Take-Up Rate	669	0.027	0.162	793	0.006	0.079	1,590	0.013	0.111	1,592	0.010	0.100
Transactions Amount (IHS)	687	0.183	1.616	816	0.000	0.000	1,674	0.048	0.807	1,651	0.011	0.321
Balance (IHS)	687	0.196	1.638	816	0.000	0.000	1,674	0.042	0.715	1,651	0.037	0.684
Saving (IHS)	667	0.201	1.649	789	0.014	0.402	1,577	0.041	0.732	1,580	0.043	0.705
Panel C: Agent Effort												
Number of Times Products are Advertised	669	0.265	2.055	793	0.057	0.591	1,587	0.187	1.085	1,589	0.053	0.331
Learned about Products from Agent	669	0.027	0.162	793	0.013	0.112	1,587	0.017	0.129	1,590	0.003	0.056
Agent Effort (PC)	669	0.009	0.053	793	0.003	0.022	1,587	0.006	0.031	1,589	0.001	0.011
Products Offered by Agent	669	0.052	0.223	793	0.014	0.117	1,587	0.047	0.211	1,590	0.022	0.147
Agent Pro-Actively Promoted Products	669	0.048	0.214	793	0.014	0.117	1,587	0.040	0.197	1,590	0.022	0.147
Agent Sales Strategy (PC)	669	0.050	0.216	793	0.014	0.117	1,587	0.043	0.200	1,590	0.022	0.147
Panel D: Trust												
Perceived Agent Earnings	664	0.551	0.498	789	0.580	0.494	1,577	0.602	0.490	1,576	0.554	0.497
Trust in Product (PC)	668	0.507	0.182	791	0.496	0.183	1,587	0.496	0.179	1,590	0.513	0.188
Trust in Bank (PC)	668	0.765	0.214	791	0.765	0.219	1,587	0.757	0.216	1,590	0.779	0.220
Trust in Agent (PC)	669	0.708	0.171	792	0.705	0.166	1,587	0.699	0.167	1,590	0.719	0.174
Trust All (PC)	669	0.592	0.149	792	0.585	0.147	1,587	0.581	0.150	1,590	0.602	0.152

Notes: Each row states the sample mean and standard deviation of the main outcome variables by each treatment group. Number of People in the Village who Take-Up is reported at the village level by scaling up the responses from the survey by the inverse of the sampling probability. All other variables are reported at the household level.

Table A.4: Main Results – Multiple Hypothesis Testing (p-values)

	(1)	(2)	(3)
	(High - Low) × Private	(High - Low) × Public	(High - Low) × (Public - Private)
Panel A. Take-up			
Take-up	0.079	0.683	0.134
Panel B. Agent Effort			
Number of Times Products are Advertised	0.050	0.010	0.437
Learned about Products from Agent	0.050	0.010	1.000
Agent Effort (PC)	0.050	0.010	0.796
Panel C. Agent Sales Strategy			
Products Offered by Agent	0.010	0.010	0.388
Agent Pro-Actively Promoted Products	0.010	0.010	0.340
Agent Sales Strategy (PC)	0.010	0.010	0.369
Panel D: Perceptions			
Perceived Agent Earnings	0.366	0.010	0.011
Trust in Product (PC)	0.515	0.010	0.022
Trust in Bank (PC)	0.812	0.010	0.088
Trust in Agent (PC)	0.812	0.010	0.022
Trust All (PC)	0.812	0.010	0.011

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. P-values are corrected using Romano and Wolf (2005)'s method. Each row is a separate regression with the dependent variables listed in the first column. "Agent Effort (PC)" and "Agent Sales Strategy (PC)" compute the first principal component from the variables in columns 1-2 and 4-5 of Table 2, respectively. "Trust in Product (PC)", "Trust in Bank (PC)", "Trust in Agent (PC)" and "Trust All (PC)" compute the first principal component from the variables in columns 2-5, 6-8, 9-12, and 2-12 of Table A.13, respectively.

Table A.5: Main Results – Extra Controls

	(1)	(2)	(3)
	(High - Low) × Private	(High - Low) × Public	(High - Low) × (Public - Private)
Panel A. Take-up			
Take-up	0.020***	0.002	−0.018**
	(0.008)	(0.004)	(0.009)
Panel B. Agent Effort			
Number of Times Products are Advertised	0.189**	0.116***	-0.073
	(0.077)	(0.027)	(0.085)
Learned about Products from Agent	0.015*	0.014***	-0.001
	(0.008)	(0.004)	(0.009)
Agent Effort (PC)	0.006**	0.004***	-0.001
	(0.002)	(0.001)	(0.003)
Panel C. Agent Sales Strategy			
Products Offered by Agent	0.035***	0.022***	-0.013
	(0.010)	(0.007)	(0.012)
Agent Pro-Actively Promoted Products	0.030***	0.015**	-0.015
	(0.010)	(0.006)	(0.012)
Agent Sales Strategy (PC)	0.033***	0.019***	-0.014
	(0.010)	(0.006)	(0.012)
Panel D. Perceptions			
Perceived Agent Earnings	-0.029	0.049***	0.078**
	(0.029)	(0.018)	(0.033)
Trust in Product (PC)	0.007	−0.019**	−0.026**
	(0.010)	(0.007)	(0.013)
Trust in Bank (PC)	-0.006	−0.026***	-0.019
	(0.014)	(0.010)	(0.017)
Trust in Agent (PC)	0.002	−0.021***	−0.023*
	(0.011)	(0.007)	(0.013)
Trust All (PC)	0.003	−0.022***	−0.025**
	(0.009)	(0.006)	(0.011)

Notes: Observations are at the household level. Each row is a separate regression with the dependent variables listed in the first column. “Agent Effort (PC)” and “Agent Sales Strategy (PC)” compute the first principal component from the variables in columns 1-2 and 4-5 of Table 2, respectively. “Trust in Product (PC)”, “Trust in Bank (PC)”, “Trust in Agent (PC)” and “Trust All (PC)” compute the first principal component from the variables in columns 2-5, 6-8, 9-12, and 2-12 of Table A.13, respectively. All regressions control for the stratification variables and for variables that differ at baseline in at least one of the pairwise comparisons across treatments (agent characteristics: has a laptop; household characteristics: female, has volunteered in the past year, knows about branchless banking, knows the agent). Standard errors are clustered at the agent level. ***p<0.01, **p<0.05, *p<0.1

Table A.6: Main Results – Weighted

	(1)	(2)	(3)
	(High - Low) × Private	(High - Low) × Public	(High - Low) × (Public - Private)
Panel A. Take-up			
Take-up	0.019**	0.001	-0.018^{*}
	(0.008)	(0.004)	(0.009)
Panel B. Agent Effort			
Number of Times Products are Advertised	0.189***	0.114***	-0.076
	(0.066)	(0.023)	(0.070)
Learned about Products from Agent	0.009	0.013***	0.005
	(0.008)	(0.005)	(0.009)
Agent Effort (PC)	0.005**	0.004***	-0.000
	(0.002)	(0.001)	(0.002)
Panel C. Agent Sales Strategy			
Products Offered by Agent	0.033***	0.025***	-0.008
	(0.010)	(0.007)	(0.013)
Agent Pro-Actively Promoted Products	0.028***	0.016***	-0.012
	(0.009)	(0.006)	(0.011)
Agent Sales Strategy (PC)	0.031***	0.021***	-0.010
	(0.010)	(0.007)	(0.012)
Panel D. Perceptions			
Perceived Agent Earnings	-0.027	0.069***	0.096**
	(0.032)	(0.023)	(0.038)
Trust in Product (PC)	0.008	-0.015	-0.023
	(0.012)	(0.010)	(0.016)
Trust in Bank (PC)	-0.004	-0.019	-0.015
	(0.018)	(0.012)	(0.021)
Trust in Agent (PC)	0.004	-0.013^{*}	-0.017
	(0.013)	(0.008)	(0.015)
Trust All (PC)	0.005	-0.017^{**}	-0.021
	(0.011)	(0.008)	(0.013)

Notes: Observations are at the household level. Each row is a separate regression with the dependent variables listed in the first column. "Agent Effort (PC)" and "Agent Sales Strategy (PC)" compute the first principal component from the variables in columns 1-2 and 4-5 of Table 2, respectively. "Trust in Product (PC)", "Trust in Bank (PC)", "Trust in Agent (PC)" and "Trust All (PC)" compute the first principal component from the variables in columns 2-5, 6-8, 9-12, and 2-12 of Table A.13, respectively. All observations are weighted inversely proportional to the probability of being sampled in a village. All regressions control for the stratification variables. Standard errors are clustered at the agent level. ***p<0.01, **p<0.05, *p<0.1

Table A.7: Take-up of Other Products

	(1)	(2)	(3)	(4)
	Take-up of Branchless Banking Products from Other Banks	Take-up of Other Financial Products	Has a Bank Account in Any Bank	Total Saving in Any Bank (IHS)
(High - Low) × Private	0.013	0.010	0.014	-0.107
	(0.008)	(0.027)	(0.027)	(0.436)
(High - Low) × Public	0.003	0.036**	0.034*	0.320
	(0.007)	(0.018)	(0.018)	(0.298)
(High - Low) × (Public - Private)	-0.010	0.026	0.019	0.428
	(0.010)	(0.032)	(0.032)	(0.527)
Regression Coefficients				
High × Private	0.013	0.010	0.014	-0.107
	(0.008)	(0.027)	(0.027)	(0.436)
High × Public	0.017**	0.034*	0.041**	0.290
	(0.007)	(0.020)	(0.021)	(0.338)
Low × Public	0.015**	-0.002	0.007	-0.031
	(0.007)	(0.021)	(0.022)	(0.360)
Observations	4639	4639	4639	4417
R-squared	0.006	0.004	0.003	0.005
Mean Dep. Var.	0.034	0.621	0.590	8.586
Mean Dep. Var. for Low × Private	0.021	0.605	0.570	8.468
p-value High × Private - High × Public	0.546	0.308	0.257	0.302
p-value High × Private - Low × Public	0.791	0.645	0.787	0.851

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. Column 1 considers take-up in other branchless banking products, different from the digital wallet and savings account. In column 2, take-up of other financial products includes house mortgage, letter of credit, business loan, vehicle loan, health insurance, etc. The variable in column 3 is a dummy variable that takes a value of one if the survey respondent has a bank account and a value of zero otherwise. Column 4 is expressed in IDR and was transformed using an inverse hyperbolic sine (IHS) transformation. ***p<0.01, **p<0.05, *p<0.1

Table A.8: Take-Up and Usage, by Product

	(1)	(2)	(3)	(4)	(5)	(6)
Product:	Savings Account			Mobile Wallet		
	Take-up	Transactions Amount (IHS)	Balance (IHS)	Take-up	Transactions Amount (IHS)	Balance (IHS)
(High - Low) × Private	0.011**	0.102**	0.098**	0.017***	0.109*	0.125*
	(0.006)	(0.051)	(0.049)	(0.006)	(0.066)	(0.067)
(High - Low) × Public	0.000	0.013	0.002	0.004	0.032	0.009
	(0.002)	(0.014)	(0.022)	(0.004)	(0.019)	(0.019)
(High - Low) × (Public - Private)	−0.011*	−0.090*	−0.096*	−0.013*	-0.077	−0.116*
	(0.006)	(0.054)	(0.054)	(0.008)	(0.067)	(0.069)
Regression Coefficients						
High × Private	0.011**	0.102**	0.098**	0.017***	0.109*	0.125*
	(0.006)	(0.051)	(0.049)	(0.006)	(0.066)	(0.067)
High × Public	-0.002	0.014	0.017	0.008**	0.043**	0.030**
	(0.002)	(0.015)	(0.015)	(0.004)	(0.018)	(0.015)
Low × Public	-0.002	0.002	0.015	0.004	0.011	0.021*
	(0.003)	(0.004)	(0.015)	(0.004)	(0.009)	(0.012)
Observations	4644	4828	4828	4644	4828	4828
R-squared	0.006	0.006	0.005	0.006	0.005	0.004
Mean Dep. Var.	0.004	0.020	0.026	0.010	0.033	0.035
Mean Dep. Var. for Low × Private	0.004	0.000	0.000	0.003	0.000	0.000
p-value High × Private - High × Public	0.016	0.102	0.115	0.175	0.328	0.163
p-value High × Private - Low × Public	0.018	0.048	0.104	0.049	0.144	0.127

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. Dependent variables in columns 2-3 and 5-6 are expressed in IDR and are transformed using an inverse hyperbolic sine (IHS) transformation. ***p<0.01, **p<0.05, *p<0.1

Table A.9: Heterogeneous Effects by Agent Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Take-up	Agent Effort (PC)	Agent Sales Strategy (PC)	Take-up	Agent Effort (PC)	Agent Sales Strategy (PC)
Panel A Sample:	Wealthy Agents			Prosocially Motivated Agents		
(High - Low) × Private	0.000	-0.002	0.013	0.003	0.001	0.018
	(0.010)	(0.002)	(0.019)	(0.008)	(0.002)	(0.015)
Panel B Sample:	Non-Wealthy Agents			Non-Prosocially Motivated Agent		
(High - Low) × Private	0.028***	0.008**	0.044***	0.031***	0.009**	0.045***
	(0.009)	(0.003)	(0.012)	(0.011)	(0.004)	(0.013)
Observations	4632	4626	4627	4632	4626	4627
% Observations in Panel A	24.81	24.79	24.79	32.73	32.75	32.74
R-squared	0.022	0.035	0.042	0.024	0.036	0.042
Mean Dep. Var.	0.013	0.004	0.032	0.013	0.004	0.032
Mean Dep. Var. for Low × Private	0.006	0.003	0.014	0.006	0.003	0.014
p-value Panel A=Panel B	0.047	0.009	0.161	0.036	0.057	0.180

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. "Agent Effort (PC)" and "Agent Sales Strategy (PC)" compute the first principal component from the variables in columns 1-2 and 4-5 of Table 2, respectively. In columns 1-3, Panel A [resp., B] restricts the observations to households in villages where the agent is more wealthy (above the 75^{th} of the index of wealth) [resp., less wealthy (below the 75^{th} of the index of wealth)]. The index of wealth is measured as a composite index of agents' assets (TV, car, microwave, refrigerator, etc). In columns 4-6, Panel A [resp., B] restricts the observations to households in villages where the agent is more prosocially motivated (volunteered in the last year) [resp., less prosocially motivated (did not volunteer in the last year)]. "p-value Panel A = Panel B" presents the p-value from the equality of the coefficients of (High-Low) × Private in Panels A and B using a fully interacted model. ***p<0.01, **p<0.05, *p<0.1.

Table A.10: Agent Tasks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Involved in Following Activity:						
	Promoting at Shop	Promoting Outside Shop	Supporting with Client Sign-ups	Dealing with Client Complaints	Providing Cash for Client's Transaction	Assisting Clients with Product Usage	Any Activity
(High - Low) × Private	0.205**	0.215***	0.192**	-0.045	-0.012	0.114	0.198***
	(0.082)	(0.074)	(0.083)	(0.062)	(0.068)	(0.082)	(0.065)
(High - Low) × Public	0.128**	0.083	0.082	0.059	0.148***	0.015	0.054
	(0.053)	(0.050)	(0.057)	(0.045)	(0.052)	(0.056)	(0.044)
(High - Low) × (Public - Private)	-0.077	-0.133	-0.111	0.104	0.160*	-0.099	−0.144*
	(0.097)	(0.089)	(0.100)	(0.076)	(0.085)	(0.099)	(0.078)
Regression Coefficients							
High × Private	0.205**	0.215***	0.192**	-0.045	-0.012	0.114	0.198***
	(0.082)	(0.074)	(0.083)	(0.062)	(0.068)	(0.082)	(0.065)
High × Public	0.230***	0.153**	0.124*	0.032	0.129**	0.027	0.147**
	(0.069)	(0.066)	(0.067)	(0.057)	(0.062)	(0.063)	(0.061)
Low × Public	0.102	0.071	0.043	-0.027	-0.019	0.012	0.092
	(0.071)	(0.067)	(0.065)	(0.054)	(0.059)	(0.064)	(0.062)
Observations	401	401	401	401	401	401	401
R-squared	0.060	0.073	0.052	0.026	0.069	0.070	0.078
Mean Dep. Var.	0.716	0.761	0.337	0.157	0.232	0.329	0.830
Mean Dep. Var. for Low × Private	0.574	0.647	0.250	0.162	0.191	0.294	0.721
p-value High × Private - High × Public	0.710	0.295	0.379	0.151	0.024	0.254	0.286
p-value High × Private - Low × Public	0.144	0.019	0.051	0.725	0.915	0.187	0.037

Notes: Observations are at the agent level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. Each outcome variable takes value of 1 if the agent reports spending some amount of time per week on the activity. "Any Activity" takes value 1 if the agent reports spending some amount of time on the branchless banking job per week and 0 otherwise. ***p<0.01, **p<0.05, *p<0.1.

Table A.11: Agent Investments

	(1)	(2)	(3)	(4)	(5)	(6)
	Invested in:					
	Bought/ Upgraded Computers	Bought a New Device with Better Internet Signal	Bought Data Plan	Made Banners/ Leaflets	Hired an Extra Employee	Other
(High - Low) × Private	0.024	0.038	0.175**	0.092	0.005	0.199**
	(0.029)	(0.057)	(0.077)	(0.062)	(0.033)	(0.088)
(High - Low) × Public	0.023	0.022	0.028	0.025	0.022	0.066
	(0.021)	(0.036)	(0.049)	(0.046)	(0.021)	(0.060)
(High - Low) × (Public - Private)	-0.001	-0.016	-0.147	-0.067	0.016	-0.132
	(0.035)	(0.067)	(0.091)	(0.076)	(0.040)	(0.106)
<u>Regression Coefficients</u>						
High × Private	0.024	0.038	0.175**	0.092	0.005	0.199**
	(0.029)	(0.057)	(0.077)	(0.062)	(0.033)	(0.088)
High × Public	0.025	0.014	0.076	0.091*	0.015	0.113
	(0.023)	(0.044)	(0.057)	(0.048)	(0.026)	(0.071)
Low × Public	0.002	-0.008	0.048	0.066	-0.007	0.046
	(0.018)	(0.042)	(0.056)	(0.047)	(0.024)	(0.071)
Observations	401	401	401	401	401	401
R-squared	0.041	0.027	0.040	0.042	0.022	0.036
Mean Dep. Var.	0.030	0.100	0.219	0.160	0.032	0.431
Mean Dep. Var. for Low × Private	0.015	0.088	0.162	0.088	0.029	0.353
p-value High × Private - High × Public	0.964	0.633	0.172	0.983	0.756	0.278
p-value High × Private - Low × Public	0.418	0.370	0.077	0.668	0.673	0.055

Notes: Observations are at the agent level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. "Bought/Upgraded Computers" takes value 1 if the agent reports investing in computers to improve their performance as an agent and 0 otherwise. "Bought a New Device with Better Internet Signal" takes value 1 if the agent reports buying a new device with better internet signal to improve their performance as an agent and 0 otherwise. "Bought Data Plan" takes value 1 if the agent reports buying data plan to improve their performance as an agent and 0 otherwise. "Made Banners/Leaflets" takes value 1 if the agent reports investing in banners to improve their performance as an agent and 0 otherwise. "Hired an Extra Employee" takes value 1 if the agent hired someone to help improve their performance as an agent and 0 otherwise. "Other" takes value 1 if the agent reports making any investments to improve their performance as an agent. ***p<0.01, **p<0.05, *p<0.1.

Table A.12: Agent Household Targeting

	(1)	(2)	(3)	(4)	(5)	(6)
	Take-up	Agent Effort (PC)	Agent Sales Strategy (PC)	Take-up	Agent Effort (PC)	Agent Sales Strategy (PC)
Panel A Sample:	Wealthy Households			Financially Literate Households		
(High - Low) × Private	0.021*	0.004**	0.033***	0.026**	0.007*	0.045***
	(0.011)	(0.002)	(0.013)	(0.010)	(0.004)	(0.016)
(High - Low) × Public	0.011	0.006***	0.030***	0.002	0.005***	0.027***
	(0.007)	(0.001)	(0.009)	(0.006)	(0.001)	(0.009)
(High - Low) × (Public - Private)	-0.010	0.001	-0.002	−0.024**	-0.001	-0.018
	(0.013)	(0.002)	(0.015)	(0.012)	(0.004)	(0.018)
Panel B Sample:	Non-Wealthy Households			Financially Illiterate Households		
(High - Low) × Private	0.019**	0.008*	0.036**	0.015*	0.005**	0.025**
	(0.009)	(0.005)	(0.015)	(0.008)	(0.002)	(0.011)
(High - Low) × Public	-0.005	0.004***	0.013	0.003	0.004***	0.014*
	(0.005)	(0.001)	(0.009)	(0.006)	(0.001)	(0.008)
(High - Low) × (Public - Private)	−0.024**	-0.004	-0.023	-0.012	-0.001	-0.011
	(0.010)	(0.005)	(0.017)	(0.010)	(0.003)	(0.014)
Observations	4644	4638	4639	4644	4638	4639
% Observations in Panel A	50.09	50.09	50.08	54.44	54.44	54.45
R-squared	0.024	0.035	0.043	0.021	0.033	0.043
Mean Dep. Var.	0.013	0.004	0.032	0.013	0.004	0.032
Mean Dep. Var. for Low × Private	0.006	0.003	0.014	0.006	0.003	0.014
p-value [(High - Low) x Private] Panel A = Panel B	0.891	0.471	0.838	0.314	0.700	0.310
p-value [(High - Low) x Public] Panel A = Panel B	0.047	0.273	0.160	0.907	0.467	0.277
p-value [(High - Low) x (Public - Private)] Panel A = Panel B	0.359	0.310	0.344	0.373	0.967	0.764

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. "Take-up" comes from the survey, and corresponds to the variable used in Table 1. "Agent Effort (PC)" and "Agent Sales Strategy (PC)" compute the first principal component from the variables in Columns 1-2 and 4-5 of Table 2, respectively. In Columns 1-3, Panel A [resp., B] restricts the observations to households that are more wealthy (above the median of the index of wealth) [resp.,less wealthy (below the median of the index of wealth)]. The index of wealth is measured as a composite index of agents assets (TV, car, microwave, refrigerator, etc). In columns 4-6, Panel A [resp., B] restricts the observations to households with high financial literacy (scored above the median number of correct finance related questions) [resp., low financial literacy (scored below the median number of correct finance related questions)]. "p-value Panel A = Panel B" presents the p-value from the equality of the coefficients in Panel A and B using the fully interacted model. ***p<0.01, **p<0.05, *p<0.1.

Table A.13: Perceptions of Potential Clients – Individual Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Product					Bank			Agent			
	Agent Pay is Commission-Based	Products are Reliable	Fees are Reasonable	Money is Safe	Product is Safe	Confidence in The Bank	Trust Banks in the Village	Contracts with Bank are Enforced	Trusts Agent	Agent is Competent	Agent is Altruistic	Agent Would not Steal Wallet
(High - Low) × Private	0.060	0.021	0.075*	0.075	-0.016	0.009	0.014	-0.069	-0.005	0.048	-0.101	0.026
	(0.051)	(0.019)	(0.043)	(0.055)	(0.023)	(0.069)	(0.042)	(0.073)	(0.071)	(0.125)	(0.148)	(0.025)
(High - Low) × Public	0.032	−0.025*	-0.024	-0.054	−0.033**	−0.109**	-0.035	−0.102**	−0.193***	-0.065	-0.147	-0.014
	(0.034)	(0.014)	(0.027)	(0.036)	(0.016)	(0.049)	(0.034)	(0.048)	(0.046)	(0.087)	(0.098)	(0.016)
(High - Low) × (Public - Private)	-0.028	−0.046*	−0.100**	−0.129*	-0.017	-0.119	-0.050	-0.033	−0.188**	-0.113	-0.047	-0.040
	(0.061)	(0.023)	(0.051)	(0.066)	(0.028)	(0.084)	(0.054)	(0.087)	(0.084)	(0.152)	(0.177)	(0.030)
Regression Coefficients												
High × Private	0.060	0.021	0.075*	0.075	-0.016	0.009	0.014	-0.069	-0.005	0.048	-0.101	0.026
	(0.051)	(0.019)	(0.043)	(0.055)	(0.023)	(0.069)	(0.042)	(0.073)	(0.071)	(0.125)	(0.148)	(0.025)
High × Public	0.066	0.013	0.064*	0.009	-0.019	-0.000	-0.057	-0.018	-0.070	0.052	-0.098	-0.010
	(0.042)	(0.016)	(0.039)	(0.049)	(0.021)	(0.060)	(0.038)	(0.057)	(0.057)	(0.110)	(0.122)	(0.023)
Low × Public	0.034	0.038**	0.089**	0.063	0.015	0.109*	-0.022	0.084	0.123**	0.117	0.049	0.004
	(0.042)	(0.017)	(0.037)	(0.048)	(0.021)	(0.061)	(0.039)	(0.060)	(0.056)	(0.111)	(0.121)	(0.023)
Observations	4828	4633	3883	4151	4633	4636	4617	4636	4639	4636	4638	4638
R-squared	0.016	0.006	0.007	0.008	0.007	0.026	0.004	0.019	0.008	0.003	0.005	0.009
Mean Dep. Var.	0.463	0.160	3.898	3.907	0.215	4.122	3.746	4.132	3.229	7.186	7.931	0.862
Mean Dep. Var. for Low × Private	0.415	0.143	3.834	3.873	0.223	4.096	3.764	4.137	3.206	7.124	7.963	0.857
p-value High × Private - High × Public	0.896	0.622	0.753	0.149	0.888	0.872	0.065	0.432	0.303	0.971	0.985	0.066
p-value High × Private - Low × Public	0.574	0.338	0.684	0.789	0.111	0.095	0.360	0.024	0.045	0.521	0.253	0.263

Notes: Observations are at the household level. In column 1, the dependent variable is equal to one if the respondent reports knowing the commission earned by the agent. Variables in columns 2 and 5 are dummies re-coded from an original scale of 1-10 (equal to 1 if the original question is greater than 8). In columns 3 and 4, variables are reversed from (ascending in level of disagreement) an original scale of 1-5 (to now ascending in level of agreement). Variables in columns 6-9 are based on their original scale of 1-5. Variables in columns 7-10 are based on their original scale of 1-10. The number of observations vary across columns because some respondents answer "don't know" and their answer is coded as missing. All regressions control for the stratification variables. Standard errors are clustered at the agent level. ***p<0.01, **p<0.05, *p<0.1

Table A.14: Long-Term Effects, Re-Scaled under Different Assumptions about γ

	(1)	(2)	(3)	(4)	(5)
	$\gamma = 0.5$	$\gamma = 0.4$	$\gamma = 0.3$	$\gamma = 0.2$	$\gamma = 0.1$
(High - Low) × Private	0.033*	0.040*	0.050*	0.068*	0.106*
	(0.019)	(0.023)	(0.028)	(0.037)	(0.055)
(High - Low) × Public	0.001	0.000	-0.000	-0.002	-0.005
	(0.011)	(0.013)	(0.016)	(0.021)	(0.032)
(High - Low) × (Public - Private)	-0.032	-0.039	-0.050	-0.069	-0.111*
	(0.022)	(0.026)	(0.032)	(0.043)	(0.063)
Regression Coefficients					
High × Private	0.033*	0.040*	0.050*	0.068*	0.106*
	(0.019)	(0.023)	(0.028)	(0.037)	(0.055)
High × Public	0.010	0.012	0.015	0.019	0.029
	(0.011)	(0.013)	(0.016)	(0.021)	(0.031)
Low × Public	0.009	0.012	0.015	0.021	0.034
	(0.011)	(0.014)	(0.017)	(0.022)	(0.032)
Observations	398	398	398	398	398
R-squared	0.061	0.061	0.061	0.061	0.061
Mean Dep. Var.	0.031	0.037	0.046	0.060	0.090
Mean Dep. Var. for Low × Private	0.018	0.022	0.027	0.035	0.050
p-value High × Private - High × Public	0.266	0.254	0.240	0.221	0.192
p-value High × Private - Low × Public	0.250	0.247	0.243	0.237	0.226

Notes: Observations are at the village level. All regressions control for stratification variables. Robust standard errors in parenthesis. Take-up is computed as the number of clients divided by the population (from our village survey). Each observation corresponds to the village-level median of monthly data between January and October 2021. We re-scaled the data to be representative of entrepreneurs and comparable to the short-term results. To do this, we compute take-up for entrepreneurs as the village-level take up rate divided by $(\alpha + \gamma * (1 - \alpha))$, where α is the share of villagers who are entrepreneurs and γ is the ratio between the take-up rate of non-entrepreneurs and the take-up rate of entrepreneurs. Each column presents the results for different assumptions on γ. ***p<0.01, **p<0.05, *p<0.1

Table A.15: Long-Term Effects on Take-Up and Usage (No Re-Scaling)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Take-Up Rate	Transaction Frequency	Transaction Frequency/Number of Clients	Balance (IHS)	Balance/Number of Clients (IHS)	Payments (IHS)	Payments/Number of Clients (IHS)
(High - Low) × Private	0.016**	35.933***	4.557	0.373*	-0.004	1.021***	0.449**
	(0.007)	(12.119)	(3.241)	(0.225)	(0.103)	(0.354)	(0.187)
(High - Low) × Public	0.000	4.815	0.303	-0.023	0.015	-0.062	0.032
	(0.006)	(10.971)	(0.809)	(0.163)	(0.073)	(0.242)	(0.115)
(High - Low) × (Public - Private)	−0.016*	−31.117*	-4.254	-0.396	0.019	−1.083**	−0.417*
	(0.009)	(16.226)	(3.523)	(0.276)	(0.127)	(0.424)	(0.218)
Regression Coefficients							
High × Private	0.016**	35.933***	4.557	0.373*	-0.004	1.021***	0.449**
	(0.007)	(12.119)	(3.241)	(0.225)	(0.103)	(0.354)	(0.187)
High × Public	0.009**	21.953**	-0.141	0.249	-0.037	0.522**	0.152
	(0.005)	(10.009)	(1.059)	(0.176)	(0.096)	(0.231)	(0.117)
Low × Public	0.009*	17.138***	-0.444	0.272	-0.052	0.584**	0.120
	(0.005)	(6.171)	(0.938)	(0.175)	(0.093)	(0.241)	(0.115)
Observations	401	401	401	401	401	401	401
R-squared	0.053	0.040	0.115	0.031	0.013	0.070	0.053
Mean Dep. Var.	0.013	24.804	2.171	0.844	0.197	1.153	0.400
Mean Dep. Var. for Low × Private	0.005	6.426	1.286	0.619	0.224	0.629	0.239
p-value High × Private - High × Public	0.394	0.352	0.197	0.567	0.719	0.155	0.113
p-value High × Private - Low × Public	0.378	0.147	0.145	0.641	0.585	0.227	0.081

Notes: Observations are the village level. Each observation corresponds to the village-level median of monthly data between January and October 2021. All regressions control for stratification variables. Robust standard errors in parenthesis. Take-up is computed as the number of clients observed in the data divided by the population (from our village survey). Columns 4 to 7 are transformed using an inverse hyperbolic sine (IHS) transformation. ***p<0.01, **p<0.05, *p<0.1.