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, but only when the incentives are unknown to prospective clients. When disclosed, higher incentives instead have no effect on take-up, 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 potential clients. In contexts with limited information about a new technology, financial incentives can thus affect technology adoption through both a supply-side effect (more agent effort) as well as a demand-side signaling effect (change in demand perceptions). Organizations designing incentive schemes should therefore pay close attention to both the level and the transparency of such incentives.

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1 Introduction

The under-utilization of new beneficial technologies is considered one of the key constraints to productivity growth (Parente and Prescott, 1994; Caselli and Coleman, 2001; Comin and Hobijn, 2004). Understanding how to increase the adoption of these technologies is thus a central issue in economics. New technologies are often promoted by local agents, who work to inform the population about their potential benefits and promote their take-up. To understand how to maximize technology adoption, one must carefully consider not only how to incentivize local agents to exert more effort in the promotion of new technologies, but also how to ensure that this extra effort translates into higher take-up. In this paper, we study the design of financial incentives offered to local agents for acquiring new clients, showing how the level of these incentives affects agent effort and technology adoption. Crucially, we examine the effects on take-up when these incentives are transparent (i.e., disclosed to the community) or not.

When disclosed, agent's financial incentives can affect 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 (*demand-side effect*). In contexts where low information and low trust in new technologies are prevalent, potential users rely on different heuristics and cues to make inferences and decide on their willingness to take up these products. Financial incentives offered to local agents for attracting new users can thus 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 bank 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 money as opposed to prosocial reasons, and hence is more likely to take advantage of an uninformed consumer (thus hampering the product's demand).[1]

If such signaling effects are present, the success of raising agents' financial incentives to boost take-up crucially depends on the transparency of the latter – i.e., the extent to which potential users are aware of the agent 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 effect on take-up by prompting agents to exert more effort without triggering any demand-side signaling effect. If, instead, incentives are public

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

information (known by the agent *and* the community), the effect of raising them on take-up is ambiguous. If higher incentives convey a positive signal about the product to potential customers, then 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 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 new branchless banking products in rural Indonesia, we find that higher financial incentives increase 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, despite the fact that agent effort increases. We show that this is explained by financial incentives conveying a negative signal about the reliability and trustworthiness of the product, the agent, and the bank to potential clients. Importantly, our results show that, in contexts with limited information and low trust about a new technology, financial incentives can affect technology adoption through a supply-side effect (agents' greater effort), but also through a demand-side signaling effect (change in demand perceptions). In such settings, organizations promoting new technologies must carefully consider the signals they send to potential clients, as these end up shaping the demand for their products. Particular attention should be paid to the transparency of financial incentives.

Our study takes place in rural East Java (Indonesia), a context that is ideally suited to study whether financial incentives affect demand perceptions through a signaling channel. The population is highly unbanked, branchless banking is largely unknown, and the level of trust in financial institutions is limited. Such characteristics mean that potential customers will rely on different heuristics (e.g., agents' incentive level) when evaluating the products' benefits and their willingness to adopt them. In addition, our setting is one in which other people's earnings are typically kept private unless explicitly revealed by an outsider. This provides us with the opportunity to create exogenous variation in pay transparency by randomizing whether potential clients are informed or not about the financial incentives paid to the agents.

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 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.[2] Stratifying by the incentive level, the second layer of the experiment introduces exogenous variation in the *transparency* of the incentives paid to the agents. 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.

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 when information on incentives is private, raising their level more than triples the take-up of new financial products, and increases the total amount of deposits/withdrawals, account balance, and savings by 18-20%. In line with an increase in agent effort, potential clients report 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.

When incentives are public information, we instead find that 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 agents responding less strongly to the incentives. In fact, they still prompt higher agent effort, even when they are public. Yet this additional effort does not translate into higher take-up due to a negative signaling effect. Using data collected on the perceptions of potential clients, we find that after learning that the agent is paid a high incentive, clients update their perception about the reliability and trustworthiness of the product, the agent,

[2] In both treatments, agents earn the same commission for clients who sign up for the digital wallet, and the same commission for each cash deposit or cash withdrawal.

and the bank downwards. As expected, the signaling effect of incentives is stronger among less knowledgeable individuals who did not know about branchless banking or who did not know the agent at baseline.

Overall, the results of this paper indicate that in contexts where information about a new technology is scarce, potential users rely on different signals in deciding whether or not to take it up. Organizations must therefore be careful of the signals they send. Particular attention should be paid to the design of incentives and the way they are disclosed. Indeed, if (as in our context) increasing financial incentives conveys a negative signal about the product, organizations seeking to maximize the take-up of new technologies would be better off raising the incentive level without, however, disclosing this information to the community. In other settings, where increasing financial incentives instead transmits a positive signal about the product, any augmentation should be disclosed to the public in order to amplify their effect.[3]

Our study complements the long-standing literature on technology adoption, which centers on identifying the driving factors of the demand for new technologies – e.g., prices (Ashraf, Berry, and Shapiro, 2010; Dupas and Cohen, 2010), credit availability (Duflo, Kremer, and Robinson, 2011), consumer knowledge and training (Cole, Sampson, and Zia, 2011; Bertrand and Morse, 2011).[4] We focus here on the role played by local agents in boosting the take-up of these new technologies. While a number of recent papers have analyzed the effect of raising local agent incentives (e.g., Ashraf, Bandiera, and Jack 2014; Ahmad et al. 2014; Aubert, de Janvry, and Sadoulet 2009; Gine, Mansuri, and Shrestha 2020), to the best of our knowledge, ours is the first to explore the combined and isolated effect of varying the level *and* the transparency of incentives on technology adoption. The diverging effects of financial incentives when they are known or not by the community is one potential explanation for why such incentives have been shown to be very cost-effective in some contexts, but less so in others.

Various theoretical studies have highlighted the role of financial incentives as signals of a product's quality or a job's attributes (Benabou and Tirole, 2003; Sliwka, 2007; Bowles and Polania-Reyes, 2012). However, the empirical evidence on the signaling value of incentives remains thin.[5] We bridge this gap by providing causal evidence that financial incentives are in

[3]Incentive disclosure can be achieved in multiple ways, e.g., job postings that prominently feature the worker's pay, announcing the agent's incentive structure along with product prices, revealing workers' pay online on a dedicated website or on a village poster, providing door-to-door information, etc.

[4]In our same study setting, Buvinic et al. (2020) show that providing financial literacy training to female entrepreneurs can increase financial inclusion. They randomize, however, at the individual level within a village, and use a sample that excludes men.

[5]Notable exceptions include Carpenter and Dolifkaa (2017) and Deserranno (2019).

themselves important signals to potential users, affecting their perception about the reliability and trustworthiness of the product and its providers, as well as influencing their demand for new technologies. Our work also relates to an emergent empirical literature that explores how people use seemingly innocuous signals as heuristics to make consequential decisions e.g., in voting (Anagol and Fujiwara, 2016; Pons and Tricaud, 2020) or the allocation of credit (Macchi, 2020).

Finally, our paper relates to previous studies on the effects of pay transparency (Mas, 2016, 2017; Cullen and Pakzad-Hurson, 2016; Perez-Truglia, 2020; Cullen and Perez-Truglia, 2020a,b; Deserranno, Kastrau, and León-Ciliotta, 2020) and disclosure norms (Cain, Loewenstein, and Moore, 2005; Bertrand and Morse, 2011). Most of this literature is interested in the effects of transparency *within* an organization, while we focus on disseminating information about pay to potential clients *outside* the organization. In a study closer to ours, Anagol, Cole, and Sarkar (2017) show that life insurance agents in India consistently provide poor advice in order to maximize their commissions. However, the disclosure of their commissions attenuates this behavior. Unlike Anagol, Cole, and Sarkar (2017), we find that revealing agents' incentives does not substantially affect their behavior, but does impact demand perceptions and, in turn, take-up of the products. We also vary the incentive level on top of its transparency, thus creating a link between the more standard literature on financial incentives and that on pay transparency.

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 Eastern Asia Pacific countries (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; Susilowati and Leonnard, 2019).

In response to this issue, in 2014 the Government of Indonesia adopted a law that establishes 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; Flaming, McKay, and Pickens, 2011; Jack and Suri, 2014; Batista and Vicente, 2019).

For the purposes of this study, 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. 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.[6]

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 side 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.

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. Agent 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 financial incentive scheme.

Agents are recruited by the bank among villagers who: (1) are the owners of a centrally 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 on-line system to be used, and marketing techniques.

[6] Unlike the digital wallet, the savings account pays an interest of 0.15%, a maximum balance of Rp. 20 million, a monthly maximum cash withdrawal or transfer of Rp. 5 million, and is insured by the government through Lembaga Penjamin Simpanan (the Indonesian version of the FDC).

2.2 Experimental Design

Our study includes 401 rural villages in five regencies (Tuban, Bojonegoro, Gresik, Ngawi, and Lamongan) of East Java. At the start of the project in November 2016, the bank was in the process of expanding its branchless banking activities in these communities (see Figure A.1).

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 research protocols).[7] The introduction of branchless banking in other areas of the country had thus far seen very low take-up levels. The bank was hypothesizing that either the level of incentives was too low to motivate agents, or that the local population had simply too little trust in the product or the bank.

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. It specifically aims to separately identify the supply- and demand-side effects of financial incentives. To this end, the experiment randomly assigns the 401 newly recruited agents into one of four treatment groups: high × public incentives (N=57), high × private incentives (N=58), low × public incentives (N=139), and low × private incentives (N=137), with the last treatment 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 demand 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

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

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). Finally, in both treatments, agents also earn the exact same commission for customers who sign up for the digital wallet account and the exact same commission for each cash deposit or cash withdrawal.[8]

To put the size of the incentives in context, in the high (low) incentives treatment, agents' earnings amount to average monthly food consumption in East Java (425,000 IDR, 2015 Central Bureau of Statistics) if 15 (22) customers sign up for the savings account and each performs 10 transactions (5 deposits above 10,000 IDR and 5 cash withdrawals under 200,000 IDR).

Public vs. Private Incentives Our setting is one in which people typically do not know one another's earning unless explicitly revealed by an outsider. In line with this, just 33% of the household respondents we interviewed at baseline declared that they knew the income of their close friends/family, only 17% were aware of the income of their distant friends/family, and a mere 11% reported believing that other villagers were aware of their own monthly income.[9,10]

In the experiment, the incentive structure of the agent was not publicized in the *private incentives* treatment (status quo), while it was publicized in the *public incentives* treatment. More precisely, each household sampled in our baseline survey was shown an information leaflet at the end of the survey. In the *private incentives* treatment, the leaflet contained information about the new savings account, the fees charged for deposits and withdrawals, and the identity/name of the agent (see Figure A.2). In the *public incentives* treatment, the leaflet contained the exact same information but also revealed the incentive earned by the agent for each client who signs up for the savings account (see Figures A.3 and A.4 for the low and high incentives, respectively). Other households in the village were contacted by

[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] In a series of hypothetical questions, 76% of respondents said that if they were to win a lottery of Rp. 500,000, they would prefer to keep this information private. What is more, 92% (83%) reported being willing to pay Rp. 100,000 (Rp. 200,000) to not share this information.

[10] Privacy norms around salary are common around the world and are referred to as the "salary taboo" (Cullen and Perez-Truglia, 2020b). Cullen and Perez-Truglia (2020b), for example, show that 69% of the employees of a very large company in Vietnam find it socially unacceptable to ask coworkers about their salary, and 89% of respondents would feel uncomfortable if they had to ask a coworker about their salary. Glassdoor (2016) presents data from a cross-country survey, which reveals that 36% of employees report not knowing their colleagues earnings.

phone by trained enumerators and given the exact same information as that provided in the leaflet (the list of these households was collected through a listing survey).

Two 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, without any mention about the level or transparency of pay. Commission amounts were only revealed to the agents once they had accepted the job and signed a contract with the bank. Meanwhile, the transparency of the incentives was never revealed to the agents (though they may have learned about it from other villagers). Reassuringly, attrition was minimal: only 9 of the original agents dropped out after the training and this number is balanced across treatments.[11] Second, throughout the experiment, we minimized spillover across treatments by limiting interactions between agents: training sessions were organized one-to-one at the agents' business and no joint meetings took place.

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) as well as a random sample of 12 potential clients per village (N=4,828), chosen from a listing of non-agricultural entrepreneurs. The survey was collected right after the agent had accepted her position (following the calendar of the two waves of recruitment). 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). At endline, we interviewed all of the respondents from our baseline survey.[12] Households were asked about take-up of the branchless banking products; the number of times the products were advertised to them by the agent, whether they learned about the products through the agent (used as a proxy of "agent effort"); and their level of trust in or perception of the reliability of the product, agent, or bank (used as measures of "client perceptions").

Administrative Data. For each household in our baseline and endline surveys, we have access to administrative records on the number of transactions (cash deposits and withdrawals) they performed from their savings account and their digital wallet, as well as the amount of each of these transactions. We also have access to the total balance in their saving

[11] These agents were replaced with the next suitable candidate.

[12] Attrition is minimal and balanced across treatments: just 16 out of 4,828 household respondents.

account and the digital wallet at endline. This dataset complements that gathered from our surveys.

2.4 Descriptive Statistics and Balance Checks

Baseline summary statistics and balance checks at the agent/village and household level are presented in Table 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 important for the proper 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 are made by phone rather than computer. Agents tend to be more educated than the average household respondent: 43% of the agents have completed a tertiary education compared to only 12% of the household respondents. Importantly, only 8% of the households had ever heard about branchless banking, confirming that this technology is indeed new to potential clients in our sample of villages.

Reassuringly, most of the variables described above are balanced across treatments. In Table 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: the high-private vs. low-private incentives treatment (column 5), the high-public vs. low-public (column 6), the high-public vs. high-private (column 7), the low-public vs. low-private (column 8). Six out of the 112 pairwise treatment comparisons presented in Table 1 appear unbalanced with a p-value below 0.1 (i.e., agent has a laptop, household respondent is a female, has volunteered in the past year, knows about branchless banking, knows the agent, and village size). We later show that all results are robust to controlling for the baseline value of these variables. The means and standard deviations of each variable by treatment groups are reported in Table A.1.

3 Empirical Strategy

Where there is imperfect information about a new technology, financial incentives can affect technology adoption by motivating agents to exert more effort (supply effect) but also by acting as a signal that influences demand-side perceptions of the quality of the product, the agent, and/or the bank (demand effect). By creating variation in both the *level* and the *transparency* of the incentives, our experiment is able to separately identify these supply and demand effects.

Throughout the paper, we use the following (pre-specified) empirical model:

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

y_{ij} is the outcome variable of interest for the potential client i in village j: i.e., in the first part of the paper, take-up and usage of branchless banking products and, in the second part of the paper, agent's effort and client perceptions. $High_j$ (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: $High_j \times Private_j$. Z_j are the stratification variables discussed above (i.e., regency fixed effects, above-median distance between the village and the closest bank branch, above-median number of households, and presence of a competing bank in the village). ϵ_{ij} are errors clustered at the village level.

When incentives are private, the difference in outcomes 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 (e.g., Lazear and Shaw, 2007), we expect higher financial incentives to increase the amount of effort agents exert in promoting the new products. Higher worker effort could, in turn, favorably influence clients' perceptions of the product's net benefit and potentially increase 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 (i.e., $(\beta_2 - \beta_3) - \beta_1 > 0$).

On the other hand, learning that an agent earns high commissions could be interpreted as a signal that the agent is primarily motivated by money (as opposed to prosocially motivated), and hence more likely to take advantage of an uninformed consumer. 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 (i.e., $(\beta_2 - \beta_3) - \beta_1 < 0$). 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 demand-side effect of financial incentives can indirectly generate a supply-side response. If, for example, high 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, or modifying their sales strategy to counteract the signaling effect (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 empirically show that this indirect supply-side response (triggered by a change in demand's perceptions) is limited in our context.

Finally, we also 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 (positive) signal, we would expect public incentives to achieve higher adoption relative to private incentives only if they are low (high). As discussed above, high public incentives may backfire when they convey a negative signal.

Identifying Assumptions The identification of the supply- and demand-side effects of financial incentives rely on two important assumptions. The first is that in the private incentives treatment, potential clients have limited information about agents' incentives. This would ensure 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 levels of the agents (supply-side). As mentioned in Section 2.2, people in our setting do not generally share information about their earnings. We furthermore 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 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; Squires, 2019). 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.[13] Reassuringly, data collected at baseline indicates that informal taxation is very limited in our context: only 3% of the surveyed respondents report that villagers ever share the proceeds of a successful business in the form of loans, favors, or gifts. Moreover, we show below that agents' effort response to the incentive level is not significantly affected by pay transparency (see Section 5.1).

4 Results: Take-up and Usage of Financial Products

4.1 Take-up

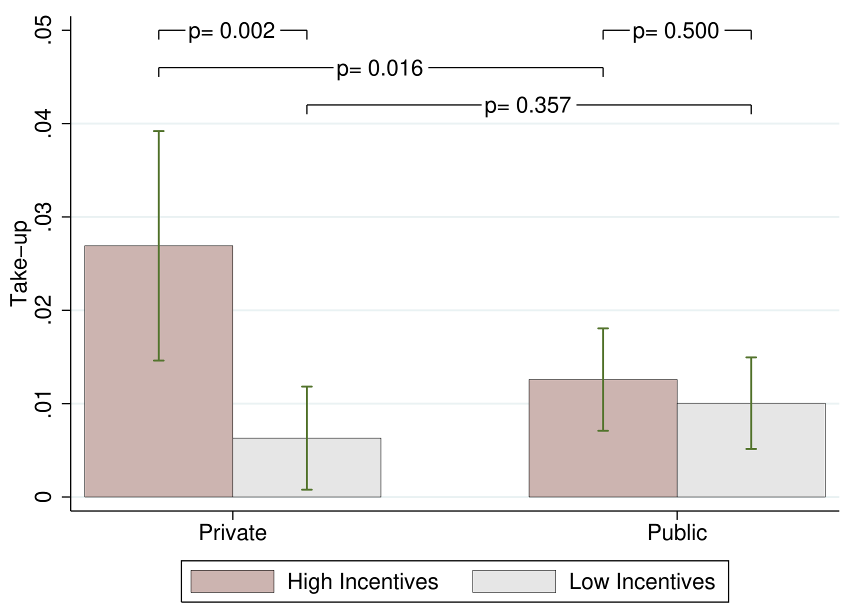
In this section, we begin by estimating the effects of our treatments on the take-up of either of the new financial products (the savings accounts or the digital wallet), and then analyze them separately. Recall that take-up is measured at endline, between 18 and 24 months after the products were introduced, by asking the sampled respondents whether they adopted the saving account or the digital wallet.

[13] As explained above, the signaling effect of the incentives impacts client perceptions and, through this, could theoretically 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 uniquely generated by this signaling effect and not by informal taxation.

We proceed in three steps. First, we plot the average take-up rate per treatment using the raw data in Figure 1. We then present the results from Equation 1 in Table 2. 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)*. Finally, as robustness checks, we present the results accounting for multiple hypothesis testing and controlling for all variables that are unbalanced across treatments at baseline (Tables A.6 and A.7, respectively). We do not discuss these last two appendix tables in the main text as the results are very similar to the main findings in Table 2.

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 1 show that the take-up rate is 0.6% at status quo, i.e., when incentives are low. When incentives are high, take-up is 4 times as high, increasing by 2.7 percentage points. The difference between the two means is statistically significant at the 1% level (p-value of 0.002).

Figure 1: 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.

Table 2 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)* $\times$ *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.

Importantly, note that although higher financial incentives cause a large increase in take-up with respect to the baseline mean, the overall share of users in the population remains low. Such a low take-up of branchless banking in the years following its introduction is not unusual. Throughout Indonesia, only 4.7% of adults report having a mobile banking account a year after its introduction, and most are residents in urban areas (Kantar, 2018). In Africa, this proportion varies considerably across countries, with large penetration (from 14% to 20%) in countries of Southern and Eastern Africa countries such as Kenya (Jack and Suri, 2014; Bharadwaj, Jack, and Suri, 2020) but substantially smaller penetration (from 0 to 4%) in countries in which these products have been more recently introduced (Niger, Nigeria, Burkina Faso, Togo, Congo, Benin, Cameroon, Guinea, Sierra Leone, Ethiopia, Malawi and Burundi) (Infomineo, 2017). Importantly, 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 total account balance and savings.

High vs. Low Incentives when Incentives are Public The last two bars of Figure 1 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 2 (second row of column 1): the coefficient *(High - Low)* $\times$ *Public* – which represents the effect of raising incentives when they are disclosed to potential clients – is close to zero and precisely 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 public incentives convey a negative signal about the quality of the product, the agent, and the bank to potential clients, which, in turn, causes a contraction in the demand for these products. Indeed, the coefficient for *(High - Low)* $\times$ *(Public - Private)* – which isolates the demand effect – is negative and statistically significant (third row of Table 2 column 1), and of the same magnitude as the supply effect. We explore this signaling effect in greater detail in Section 5.2, where we show how potential clients' perceptions change when higher agents' 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 turn to assessing the causal effect of publicly disseminating information about the agent's incentives, holding the incentive level fixed.

Our results suggest that it is in the bank's best interest to avoid publicizing information about high-powered incentives to potential clients. As shown in the pink bars of Figure 1 and in the bottom panel of Table 2, 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, and hence reduce demand.

Interestingly, when incentives are instead 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.

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. Once clients sign up for the products, they may indeed become knowledgeable about their benefits and use them more frequently (akin to an experience good, see e.g., Bryan, Chowdhry, and Mobarak 2014).

To measure account usage, we employ administrative data on the total amount involved in cash-ins and cash-outs from branchless banking accounts between baseline and endline, as well as the total balance in these accounts at endline. 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. 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 IDRs, we use inverse hyperbolic sine transformations (IHS) to deal with data skewness, while retaining the zeros (Johnson, 1949; Friedline, Masa, and Chowa, 2015).

When incentives are kept private, paying the branchless banking agents a higher incentive for take-up increases product usage: the total transactions amount goes up by 18.4% and the total balance increases by 19.6%. These results are in line with those on take-up, and are presented in columns 2-4 of Table 2. Importantly, savings in the branchless banking account also significantly increase by 19.1%.

Overall, when incentives are kept private, raising their level not only boosts take-up, but also increases the use of these products, which results in greater savings. When, in contrast, incentives are made public, raising their level neither increases take-up, nor impacts 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.2, 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.2 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. 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. Indeed, this is not surprising: if the higher incentive generates a drop in trust in the agent or the bank (as we document in Section 5.2), this should negatively 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 *other banks*. One concern is that an 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.3 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 in formal bank accounts (column 4).[14]

[14] Table A.3 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.

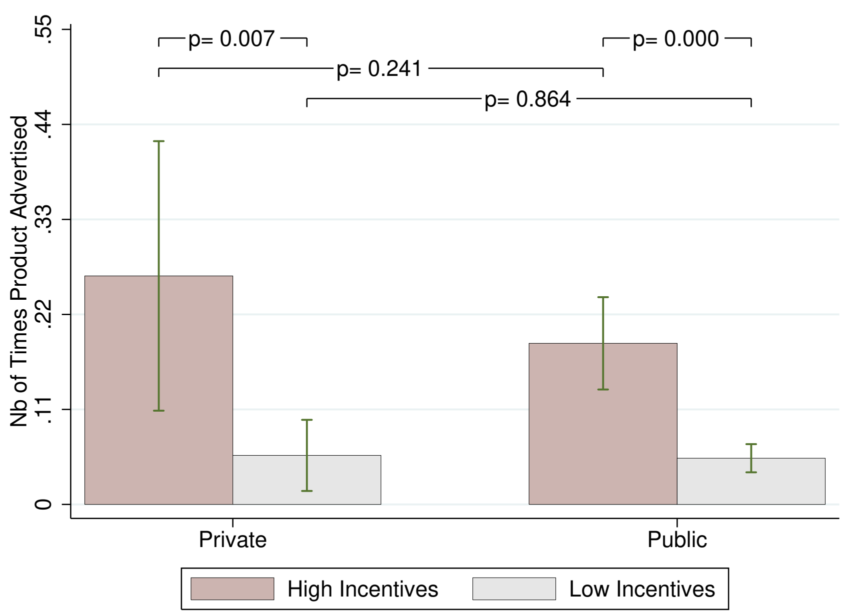
5 Supply and Demand Effects of Financial Incentives

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. As before, we begin by presenting the results using the raw data in Figure 2 and then our regression results in Table 3.

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. Figure 2 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 the public treatment (although slightly higher in the former, the difference is not statistically significant with a p-value of 0.359). This implies that the public availability of information about agent compensation did not affect the effort response to the incentives. This is consistent with agents not internalizing or reacting to the signaling effect of public information, as well as with the assumption that informal taxation is limited in this setting and that agents are the residual claimants of their effort.

Figure 2: 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). Top horizontal bars show p-values for t-tests of equality of means between different treatment groups.

In Table 3, we estimate Equation 1 and extend the list of outcomes used to measure agent effort. High-private incentives prompt agents to advertise the products 4.56 times more often to potential clients relative to low-private incentives (column 1). Similarly, we find that households are 2.15 times more likely to have learned about the products from the agent (column 2).[15] 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-private relative to the low-private treatment.

A similar boost in agent effort is observed in the high-public incentives treatment. As in Figure 2, this increase occurs independent of 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 3, columns 4-6, we study a second dimension of agent's 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 explicitly 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 private incentives treatment than in the low private one (column 4), and 2.4 times more likely to proactively try to complete the sale (column 5). Results are similar if we use the first principal component of these two "sales strategy" variables (column 6). Again, these effects are comparable in the public and private treatments.

Table 4 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. In Table 4 (columns 1-3), we present the results on agent effort separately for two types of agents: those with a baseline asset index above the median in Panel A ("more wealthy") and those below the median in Panel B ("less wealthy"). We do the same in columns 4-6, but divide the agents based on whether or not they had been involved in a voluntary activity in the last year; Panel A indicating the "more prosocially motivated" agents and Panel B the "less prosocially motivated." For ease of interpretation, we only show the coefficient associated with the supply-side channel in the absence of any signaling effect (i.e., *(High - Low)* $\times$ *Private*). In addition, we estimate a fully interacted model and report the p-value of equality of the effects for more vs. less wealthy or more vs. less prosocially

[15] 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.

motivated agents at the bottom of the table (see "p-value Panel A=Panel B"). The increase in agents' effort is shown to be entirely concentrated among the poorest and the least pro-socially motivated agents (columns 2 and 5). Accordingly, the take-up of the new financial products increases only for these agents (columns 1 and 4).

Finally, while public information does not seem to affect the total level of effort exerted by the agents when incentives increase, one possibility is that it does impact their targeting decisions: e.g., in the public treatment, agents who earn a higher incentive may concentrate their effort on certain customers for whom they believe the signaling effect is less strong. For example, people who already know the agent, trust her or know the product well at baseline and who are less likely to update their perception downwards upon learning about agents' high incentive level (we will show this is indeed the case in Section 5.2). Table A.4 analyzes whether, in the public treatment, raising the level of incentives increases the extent to which agents' target these "knowledgeable" clients more than in the private treatment. We do this by presenting the difference-in-difference effect *(High - Low)* $\times$ *(Private-Public)* on agent effort for respondents who know/trust the agent or the product at baseline (Panel A) and those who do not (Panel B). The lack of difference in the coefficients across panels indicates that differential targeting between the private and public treatment is non-existent in our context (see "p-value Panel A=Panel B" estimated from a fully interacted model in columns 1-2, 6-7 and 11-12).

In sum, agents respond strongly to higher incentive levels, especially the poorest and those of lower pro-social motivation. In contrast, they do not respond to the transparency of incentives.

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 signal conveyed by high incentives, which adversely affects the demand for the new financial products.

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.[16] 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 3, using the principal component that combines all questions about trust (product, agent, and bank). 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 only marginally significant (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).[17]

In Table 5, 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.[18]

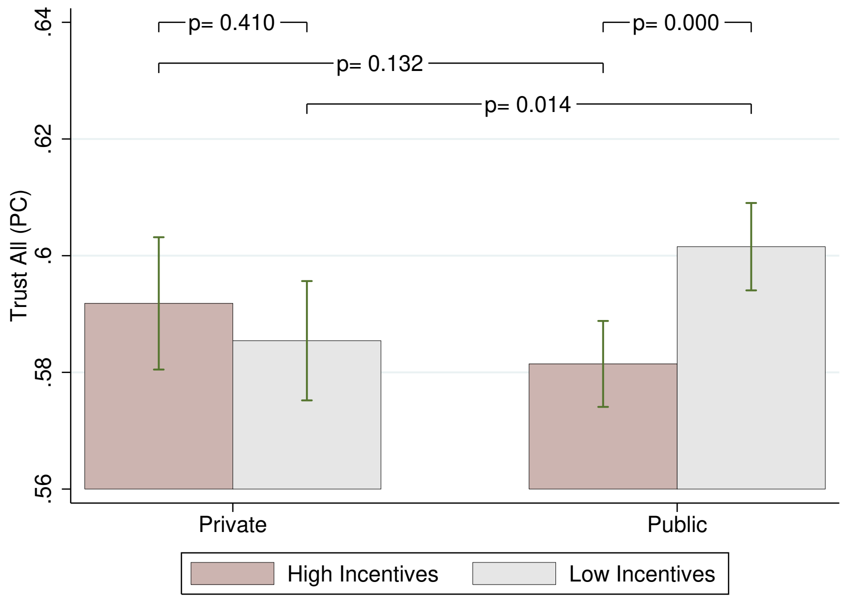
Column 1 of Table 5 shows that in the high incentives treatment, household respondents are 5

[16]The results for each individual question are shown in Table A.5. 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 scale 1 to 10, how competent 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?*

[17]This evidence suggests 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.

[18]All respondents were told that there are no fees to open the account, no minimum deposit and balance, and that all transactions are performed by the agent (see Figures A.2, A.3 and A.4). They were also informed about the fees charged per transaction (cash-in/cash-out) and, orally, the name of the agent and the interest rate associated with the savings account.

Figure 3: Potential Clients' Perceptions: 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.

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)* × *Public*).[19] When incentives are private, perceived agents' earnings do not vary with the actual incentives paid (see coefficient *(High - Low)* × *Private*). This result confirms that, in our setting, information about agent earnings does not diffuse in the village unless households are informed about it by an outsider.

In columns 2-4 of Table 5 we show that, when incentives are public, higher levels elicit lower trust in the product, in the bank, and in the agent (row 2). This effect is driven both by people in the low-public treatment updating their beliefs about the trustworthiness of the product and its providers upwards, and by people in the high-public treatment updating their perceptions downwards. When private, higher incentives instead do not affect trust in the product, the bank, or the agent, as expected.

The third row of Table 5 isolates the signaling effect of higher public financial incentives on potential clients' perceptions. We find a strong negative and significant effect. This effect

[19]The effect is driven both by more people in the high (public) treatment believing that the compensation is fair or generous and more people in the low (public) treatment believing that the incentives are too low.

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), it is impossible to pin down precisely which of the dimensions of trust matter more in our context.[20]

Table A.5 examines each individual perception question separately and shows that both the product's perceived reliability and its safety decline with higher public incentives (columns 1 and 4, respectively). High public incentives also reduce trust in contract enforcement in general and thus trust in the overall banking system (column 7). Finally, perceived trustworthiness, competence, and pro-sociality of the agent all go down with higher public incentives (columns 8-11).

Lastly, we explore the heterogeneous effect of our treatments on perceptions by client characteristics. One would expect the signaling effect to be mostly driven by potential clients who have less information and trust about the agent and the products, while the effect should be smaller (or muted) for more informed people who do not need to rely on external signals to form their opinions about the product. As expected, Table 6 shows that the negative effect of publicizing high incentives on client perceptions is concentrated among respondents who do not know or do not trust the agent at baseline, and those who do not know what branchless banking is at baseline (columns 2, 4 and 6).[21]

In sum, the results of this section indicate that agent incentives are used as a heuristic to derive conclusions about the products, the bank, and the agent, and – as shown in Section 4 – ultimately affect take-up. In particular, informing potential clients about the agent's high (or low) incentives reduces (increases) their levels of trust in the bank, the agent, and the product, in turn reducing (boosting) their demand. These effects are stronger among customers who have less information about the agent and the product, who have to rely more on heuristics and (as expected) update their perceptions to a greater degree. Our 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 Tirole, 2003). Likewise, they align with a recent literature documenting how people rely on seemingly innocuous observable cues to make consequential economic decisions (Pons and Tricaud, 2020; Macchi, 2020).

[20] All the results of this section are robust to accounting for multiple hypothesis testing (Table A.6) and to controlling for all variables that are unbalanced across treatments at baseline (Table A.7, column 2).

[21] For ease of exposition, we only report the coefficient representing the demand-side effects: *(High - Low)* $\times$ *(Public - Private)*. At the bottom of the table, we provide the p-value for the difference in the relevant coefficients between the two panels. For completeness, we also report the effects on take-up (columns 1, 3 and 5).

6 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 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 completely muted. Interestingly, this is not explained by agents responding less strongly to public incentives. Indeed, even when they are public, the incentives still prompt more effort on the part of the agent. Due, however, to a negative signaling effect of high incentives, this extra effort does not translate into greater take-up. We show that potential clients update their perceptions of the quality and trustworthiness of the product downwards after learning that the agent is paid a high incentive, thus effectively reducing the products' demand. In contrast, they update their perceptions upwards after learning that the agent is paid a low incentive.

Our results reinforce previous evidence in the literature on the effectiveness of financial incentives in prompting frontline workers to exert more effort (e.g., Ashraf, Bandiera, and Jack 2014; Ahmad et al. 2014; Aubert, de Janvry, and Sadoulet 2009; Gine, Mansuri, and Shrestha 2020). Crucially, however, we argue that in contexts where information about new technologies is limited, and potential users accordingly rely on different observable cues to inform their willingness to take them up, public information about financial incentives provides a meaningful signal about the quality and trustworthiness of the product. In our setting, the positive effects of higher agent incentives on take-up only materialize if these incentives are kept private. When they become 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.

From a policy standpoint, organizations promoting new technologies need to carefully consider the signals they send to potential clients, as these end up shaping the demand for their products. Specific attention should be paid to the transparency of financial incentives along with their level. High incentives should be kept private information whenever these convey a negative signal to potential clients. In contrast, where low financial incentives convey a positive signal, they should be disclosed to the community.

Our results are particularly important for the design of financial incentives in markets where the product's characteristics are not directly observable by consumers. Take, for example, pharmaceutical products, medical services, or credence goods (Balafoutas and Kerschbamer, 2020). In these markets, information about promoter's incentives may convey signals that ultimately inform consumer decisions. If these signals negatively affect consumers' perceptions, financial incentives become ineffective or can even backfire. This is not to say that financial incentives cannot be effective in other contexts. They certainly are and have been shown to be in markets where the product's characteristics are easily observable and well-known to customers. In these markets, financial incentives do not play such a signaling role and their transparency may less crucially matter.

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Table 1: Summary Statistics and Balance Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Obs.	Mean	Std. Dev.	p-value F-stat Joint	p-value (High-Low)× Private	p-value (High-Low)× Public	p-value (Public-Private)× High	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: Each row states the 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. 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. Low × Public in column 7, High × Private vs. Low × Private in column 8. ***p<0.01, **p<0.05, *p<0.1

Table 2: Take-up and Usage

	(1)	(2)	(3)	(4)
	Take-up	Transactions Amount (IHS)	Balance (IHS)	Saving (IHS)
(High - Low) × Private	0.021^{***}	0.184^{**}	0.196^{**}	0.191^{**}
	(0.008)	(0.078)	(0.078)	(0.078)
(High - Low) × Public	0.003	0.036	0.003	0.001
	(0.004)	(0.023)	(0.027)	(0.025)
(High - Low) × (Public - Private)	-0.018^{**}	-0.148^{*}	-0.193^{**}	-0.190^{**}
	(0.009)	(0.081)	(0.082)	(0.081)
Regression Coefficients				
High × Private	0.021^{***}	0.184^{**}	0.196^{**}	0.191^{**}
	(0.008)	(0.078)	(0.078)	(0.078)
High × Public	0.006	0.049^{**}	0.039^{*}	0.029
	(0.005)	(0.022)	(0.020)	(0.024)
Low × 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 × Private	0.006	0.000	0.000	0.014
p-value High × Private - High × Public	0.048	0.094	0.049	0.041
p-value High × Private - Low × 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 administrative data. ***p<0.01, **p<0.05, *p<0.1

Table 3: 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 4: 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:	More Wealthy Agents			More 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:	Less Wealthy Agents			Less 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	0.029	0.027	0.032	0.022	0.039	0.040
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 3, respectively. In columns 1-3, Panel A [resp., B] restricts the observations to households in villages where the agent is more wealthy (above the median index of wealth) [resp., less wealthy (below the median 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 in Panel A and B using the fully interacted model. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Potential Clients' Perceptions

	(1) Perceived Agent Earnings	(2) Trust in Product (PC)	(3) Trust in Bank (PC)	(4) Trust in Agent (PC)	(5) 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. "Perceived Agent Earnings" is the respondents' perceptions about the earnings of the agent. "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 1-4, 5-7, 8-11 and 1-11 of Table A.5, respectively. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Heterogeneous Effects by Respondents' Trust and Knowledge

	(1)	(2)	(3)	(4)	(5)	(6)
	Take-up	Trust All (PC)	Take-up	Trust All (PC)	Take-up	Trust All (PC)
Panel A Sample:	Friends or Family of the Agent		Trust the Agent's Financial Advices		Know Branchless Banking	
(High - Low) × (Public - Private)	-0.023	0.001	-0.035	-0.006	-0.040	-0.013
	(0.017)	(0.019)	(0.034)	(0.038)	(0.048)	(0.036)
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)	-0.015	-0.033^{***}	-0.017^{**}	-0.025^{**}	-0.015^{*}	-0.025^{**}
	(0.010)	(0.012)	(0.008)	(0.011)	(0.008)	(0.011)
Observations	4644	4638	4644	4638	4644	4638
% Observations in Panel A	25.62	25.61	8.40	8.41	8.07	8.09
R-squared	0.026	0.944	0.060	0.944	0.076	0.947
Mean Dep. Var.	0.013	0.591	0.013	0.591	0.013	0.591
Mean Dep. Var. for Low × Private	0.006	0.585	0.006	0.585	0.006	0.585
p-value Panel A=Panel B	0.683	0.117	0.576	0.629	0.601	0.741

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. "Trust All (PC)" computes the first principal component from the variables in columns 1-11 of Table A.5. In columns 1-2, 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 3-6 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. "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.

Appendix Figures and Tables

Figure A.1: Map of Villages in the Study Sample, by Treatment Status

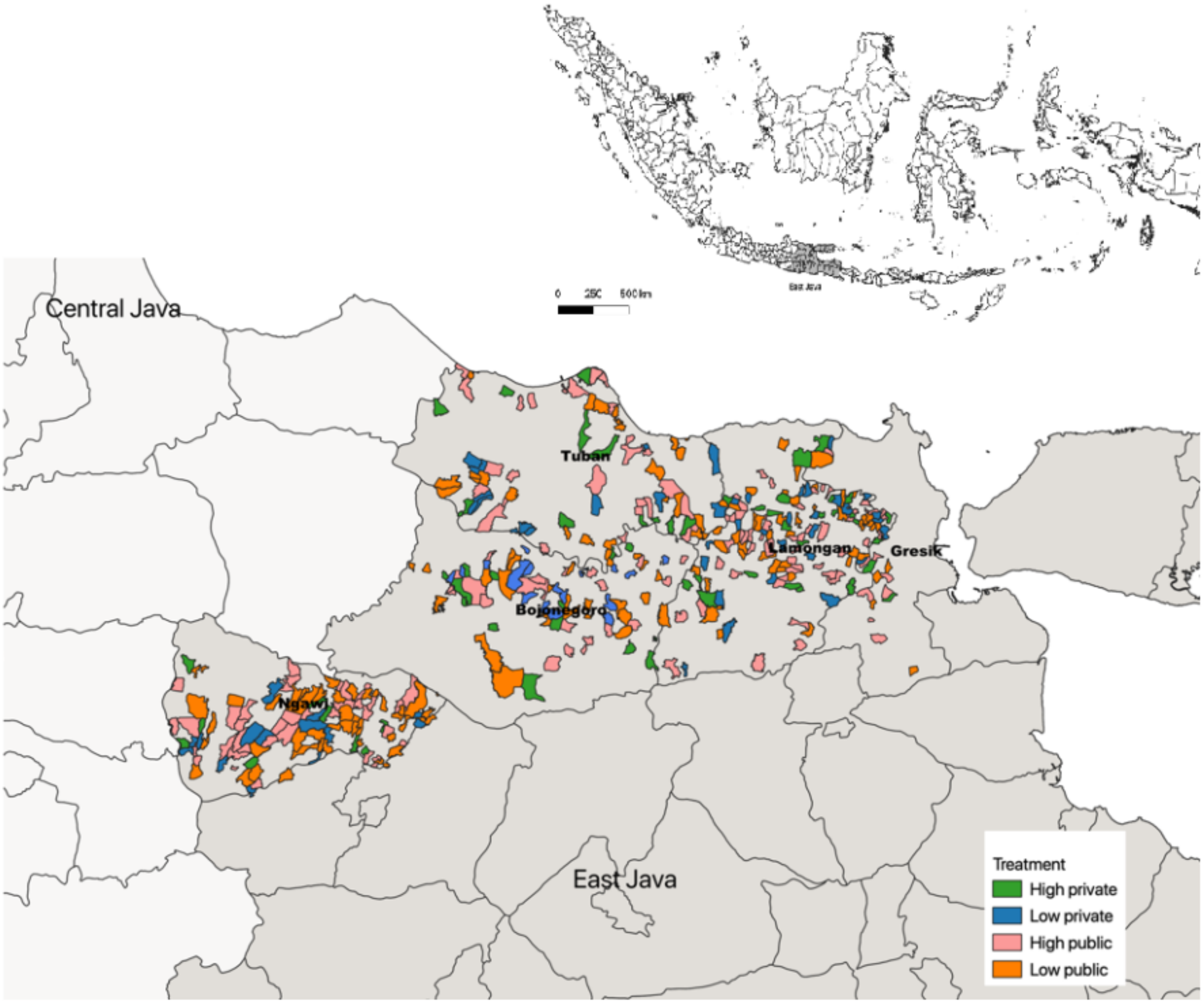


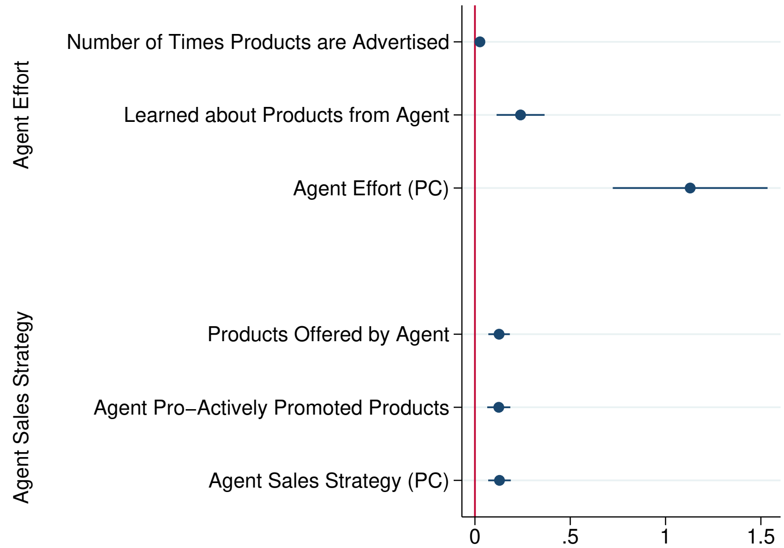
Figure A.2: Leaflet for the Private Incentives Treatment

Figure A.3: Leaflet for the Public & Low Incentives Treatment

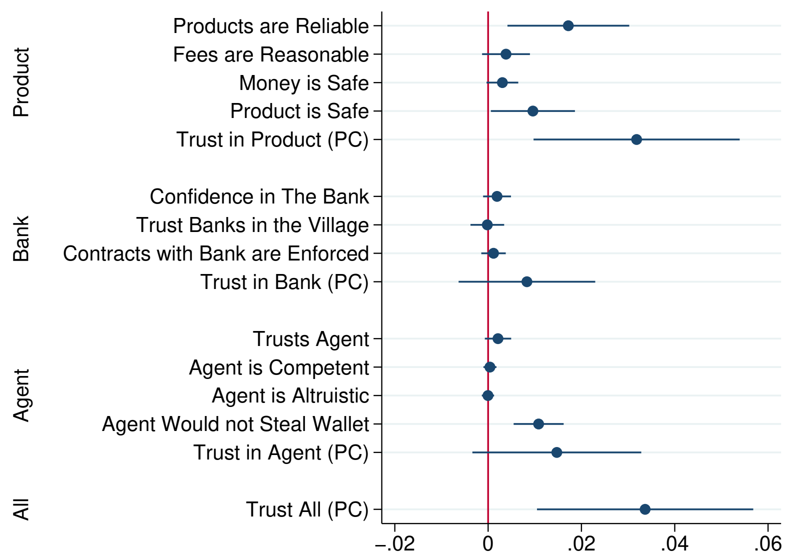
Figure A.4: Leaflet for the Public & High Incentives Treatment

Figure A.5: Correlation of Take-up with Agent Effort and Client Perceptions

(a) Correlation Take-up and Agent Effort



(b) Correlation Take-up and Client Perceptions



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

Table A.1: Summary Statistics by Treatment

	(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 sample mean and standard deviation for village-level variables in Panel A, agent-level variables in Panel B, and household-level variables in Panel C.

Table A.2: 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.3: 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 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. ***p<0.01, **p<0.05, *p<0.1

Table A.4: Heterogeneous Effects by Respondents' Trust and Knowledge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Agent Effort (PC)	Agent Sales Strategy (PC)	Trust in Product (PC)	Trust in Bank (PC)	Trust in Agent (PC)	Agent Effort (PC)	Agent Sales Strategy (PC)	Trust in Product (PC)	Trust in Bank (PC)	Trust in Agent (PC)	Agent Effort (PC)	Agent Sales Strategy (PC)	Trust in Product (PC)	Trust in Bank (PC)	Trust in Agent (PC)
Panel A Sample:	Friends or Family of the Agent					Trust the Agent's Financial Advices					Know Branchless Banking				
(High - Low) × (Public - Private)	0.003	-0.012	-0.000	0.003	-0.004	-0.015	0.052	-0.005	-0.014	0.004	-0.020	-0.089	0.031	-0.025	-0.056
	(0.004)	(0.030)	(0.022)	(0.027)	(0.023)	(0.018)	(0.046)	(0.049)	(0.046)	(0.039)	(0.023)	(0.057)	(0.043)	(0.051)	(0.042)
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)	-0.003	-0.014	-0.036^{**}	-0.024	-0.027^{*}	0.001	-0.019	-0.026^{**}	-0.018	-0.023^{*}	0.001	-0.008	-0.030^{**}	-0.017	-0.019
	(0.004)	(0.012)	(0.014)	(0.020)	(0.014)	(0.002)	(0.012)	(0.013)	(0.018)	(0.013)	(0.002)	(0.011)	(0.013)	(0.018)	(0.013)
Observations	4638	4639	4636	4636	4638	4638	4639	4636	4636	4638	4638	4639	4636	4636	4638
% Observations in Panel A	25.64	25.63	25.63	25.63	25.61	8.41	8.41	8.41	8.41	8.41	8.09	8.08	8.09	8.09	8.09
R-squared	0.065	0.074	0.886	0.936	0.951	0.076	0.122	0.873	0.947	0.957	0.080	0.118	0.891	0.937	0.953
Mean Dep. Var.	0.004	0.032	0.504	0.767	0.708	0.004	0.032	0.504	0.767	0.708	0.004	0.032	0.504	0.767	0.708
Mean Dep. Var. for Low × Private	0.003	0.014	0.496	0.765	0.705	0.003	0.014	0.496	0.765	0.705	0.003	0.014	0.496	0.765	0.705
p-value Panel A=Panel B	0.240	0.965	0.165	0.379	0.336	0.371	0.134	0.673	0.924	0.505	0.386	0.150	0.163	0.872	0.363

Notes: Observations are at the household level. All regressions control for the stratification variables. Standard errors are clustered at the agent level. "Trust in Product (PC)," "Trust in Bank (PC)," and "Trust in Agent (PC)" compute the first principal component from the variables in columns 1-4, 5-7 and 8-11 of Table A.5, respectively. "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 3, respectively. In columns 1-5, Panel A [resp., B] restricts the observations to households in villages where the respondent is friend or family of the agent at baseline [resp., respondent is not friend or family of the agent)]. Columns 6-15 are similarly divided relative to whether the respondent trusts the agent's financial advice at baseline and whether the respondent knows about branchless banking at baseline. "p-value Panel A = Panel B" presents the p-value from the equality of the coefficients in Panel A vs. B using the fully interacted model. ***p<0.01, **p<0.05, *p<0.1.

Table A.5: Potential Clients' Perceptions – Individual Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Product				Bank			Agent			
	Products are Reliable	Fees are Reasonable	Money is Safe	Product is Safe	Confidence in The Bank	Trust Banks in the Village	Contracts with Banks are Enforced	Trusts Agent	Agent is Competent	Agent is Altruistic	Agent Would not Steal Wallet
(High - Low) × Private	0.021	0.075*	0.075	-0.016	0.009	0.014	-0.069	-0.005	0.048	-0.101	0.026
	(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	−0.025*	-0.024	-0.054	−0.033**	−0.109**	-0.035	−0.102**	−0.193***	-0.065	-0.147	-0.014
	(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)	−0.046*	−0.100**	−0.129*	-0.017	-0.119	-0.050	-0.033	−0.188**	-0.113	-0.047	-0.040
	(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	0.021	0.075*	0.075	-0.016	0.009	0.014	-0.069	-0.005	0.048	-0.101	0.026
	(0.019)	(0.043)	(0.055)	(0.023)	(0.069)	(0.042)	(0.073)	(0.071)	(0.125)	(0.148)	(0.025)
High × Public	0.013	0.064*	0.009	-0.019	-0.000	-0.057	-0.018	-0.070	0.052	-0.098	-0.010
	(0.016)	(0.039)	(0.049)	(0.021)	(0.060)	(0.038)	(0.057)	(0.057)	(0.110)	(0.122)	(0.023)
Low × Public	0.038**	0.089**	0.063	0.015	0.109*	-0.022	0.084	0.123**	0.117	0.049	0.004
	(0.017)	(0.037)	(0.048)	(0.021)	(0.061)	(0.039)	(0.060)	(0.056)	(0.111)	(0.121)	(0.023)
Observations	4633	3883	4151	4633	4636	4617	4636	4639	4636	4638	4638
R-squared	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.	0.160	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	0.143	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	0.622	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	0.338	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. 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.6: Main Results Adjusting for Multiple Hypothesis Testing

	(1)	(2)	(3)
	(High - Low) × Private	(High - Low) × Public	(High - Low) × (Public - Private)
Take-up	0.079	0.683	0.141
Agent Effort			
Number of Times Products are Advertised	0.050	0.010	0.527
Learned about Products from Agent	0.050	0.010	1.000
Agent Effort (PC)	0.050	0.010	0.882
Agent Sales Strategy			
Products Offered by Agent	0.010	0.010	0.462
Agent Pro-Actively Promoted Products	0.010	0.010	0.419
Agent Sales Strategy (PC)	0.010	0.010	0.430
Client Perceptions			
Perceived Agent Earnings	0.366	0.010	0.010
Trust in Product (PC)	0.515	0.010	0.021
Trust in Bank (PC)	0.812	0.010	0.041
Trust in Agent (PC)	0.812	0.010	0.021
Trust All (PC)	0.812	0.010	0.010

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 3, 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 1-4, 5-7, 8-11, and 1-11 of Table A.5, respectively.

Table A.7: Main Results With Extra Controls

	(1)	(2)	(3)
	Take-up	Agent Effort (PC)	Trust All (PC)
(High - Low) × Private	0.020***	0.006**	0.003
	(0.008)	(0.002)	(0.009)
(High - Low) × Public	0.002	0.004***	−0.022***
	(0.004)	(0.001)	(0.006)
(High - Low) × (Public - Private)	−0.018**	-0.001	−0.025**
	(0.009)	(0.003)	(0.011)
Regression Coefficients			
High × Private	0.020***	0.006**	0.003
	(0.008)	(0.002)	(0.009)
High × Public	0.004	0.003**	-0.003
	(0.004)	(0.001)	(0.008)
Low × Public	0.002	−0.002**	0.019**
	(0.004)	(0.001)	(0.008)
Observations	4632	4626	4626
R-squared	0.014	0.019	0.024
Mean Dep. Var.	0.013	0.004	0.591
Mean Dep. Var. for Low × Private	0.006	0.003	0.585
p-value High × Private - High × Public	0.037	0.190	0.429
p-value High × Private - Low × Public	0.016	0.001	0.026

Notes: Observations are at the household level. 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. "Agent Effort (PC)" computes the first principal component from the variables in columns 1-2 of Table 3. "Trust All (PC)" computes the first principal component from the variables in columns 1-11 of Table A.5. ***p<0.01, **p<0.05, *p<0.1.