Intrinsic Motivation and Referrals Within Firms: Evidence from a Large Microfinance Institution *

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August 26, 2024

Abstract

Many organizations rely on internal referrals between employees with differing comparative advantages. Yet when an employee encounters a lucrative opportunity, they may be motivated to retain it even when doing so harms efficiency. We develop a framework that incorporates this tension and characterize optimal referral contracts. When agents are intrinsically motivated, a fixed-price referral contract is optimal, while otherwise a revenue-sharing referral contract is optimal. We implement a field experiment to evaluate these contracts in a large microfinance institution that has both microcredit and a larger "graduation loan." Both contracts induce microcredit officers to refer more borrowers to the graduation portfolio. Relative to those endorsed before the contract changes, borrowers endorsed afterwards exhibit better repayment in graduation loans and their businesses grow more upon receiving graduation loans. Consistent with the theory, the fixed-price (revenue-sharing) contract performs better for loan officers with high (low) intrinsic motivation. Finally, utilizing existing and novel data on the organizational practices of microfinance institutions around the world, we document that about half of all microfinance institutions have internal graduation programs and of these 48% employ the same compensation practices as our partner lender did prior to the experiment.

*We thank Daniela Aizencang, Carolina Allende, Tomás Alburquerque, Shreya Chandra, Ana Paula Franco, Rafael Tiara, and Astha Vohra for outstanding research assistance on this project. We are grateful to Nava Ashraf, Oriana Bandiera, Abhijit Banerjee, Iwan Barankay, Arielle Bernhardt, Emily Breza, Shawn Cole, Bob Gibbons, Dean Karlan, Asim Khwaja, Cynthia Kinnan, Scott Kominers, Dominic Leggett, Rocco Macchiavello, Charity Troyer Moore, Ben Olken, Rohini Pande, Michael Powell, Andrea Pratt, Antoinette Schoar, Jesse Shaprio, Chris Woodruff, and Daniel Xu for helpful discussions. This project was implemented in collaboration with J-PAL Latin America and the Caribbean. We also thank the HBS Latin America Research Center for support. This project is registered in the AEA RCT Registry (AEARCTR-0004963) and was approved by IRB at Harvard University. Financial support for this project was provided by Harvard University.

1 Introduction

Many organizations rely on internal referrals between employees with differing comparative advantages. In professional service partnerships – law, accounting, consulting firms and the like – the partner who first engages a client may not be best positioned to serve them. A salesperson who receives an inbound customer may not be best equipped to close the deal. As employees develop skills and experience, managers often realize they should be promoted, potentially working under a new manager. In each of these settings, it may be in the interest of the person who observes the opportunity to retain it, even if they are not best positioned to do so. For instance, hoping to earn a large commission, a rookie salesperson who encounters a potentially lucrative customer may attempt to make the sale rather than referring it to a more experienced colleague. And a manager with a skilled employee on their team may defer promotion if doing so would imply moving the employee to a new team and reducing the manager's performance-based compensation. In such settings, how should organizations compensate employees to induce efficient referrals?

To explore this question, we implemented a field experiment in collaboration with one of Chile's largest microfinance institutions. In addition to standard microcredit, our partner lender has an internal graduation program. Borrowers who graduate from the microcredit portfolio are offered larger, more flexible graduation loans. Critically, at the time of our study, the loan officers who managed the microloans were non-overlapping with the loan officers who managed the graduation loans. Thus, one route for a borrower to graduate to larger loans is that their microcredit loan officer referred them to the appropriate graduation loan officer.

One deterrent to efficient referrals is that borrowers who are suitable for graduation loans are typically good performers in the microcredit portfolio. As loan officers are rewarded for the size and performance of their portfolio, microcredit loan officers have an incentive to retain their best borrowers rather than referring them. The aim of this paper is to characterize this incentive conflict and evaluate potential solutions.

To structure our empirical investigation and motivate our experimental interventions we develop a theoretical framework based on Garicano and Santos (2004). A firm employs two agents: a microcredit officer and a graduation officer. The microcredit officer encounters borrowers and receives a private signal about each borrowers' type. Low-type borrowers should remain in the microcredit portfolio, and high-type borrowers are more efficiently served in the graduation portfolio. However, high-type borrowers are more profitable than low-type borrowers in both portfolios. The microcredit officer then chooses whether to refer the borrower to the graduation officer or not, in which case the borrower will remain in the microcredit portfolio. Whichever loan officer receives the borrower must then exert effort to collect repayment.

Our primary departure from Garicano and Santos (2004) is to introduce intrinsic motivation, or social preferences. Specifically, we assume that the low-skill agent partially internalizes social welfare, and we study comparative statics based on the strength of this preference. This is an important feature of our empirical context, as it has been well-documented that intrinsic motivation and social preferences are important for many employees in the social sector (e.g. Ashraf et al., 2014, 2019). And even beyond the social sector, there is evidence that social preferences play an important role in productivity and effort provision (e.g. Bandiera et al., 2005; Bandiera et al., 2010).

The firm's problem is to choose a referral contract that maximizes output subject to incentive constraints. The key tradeoff is a tension between the strength of the microcredit officer's incentive to make efficient referrals and the strength of the graduation officer's incentive to exert effort in recovery. The larger is the microcredit officer's payout when a referred borrower performs well in the graduation portfolio, the more incentivized they will be to refer high-type borrowers. But also, the larger the share of revenue allocated to the microcredit officer for referred borrowers in the graduation portfolio, the less revenue is left to incentivize the graduation officer to exert effort.

Our main result is that when the microcredit officer is sufficiently intrinsically motivated, the optimal referral contract takes the form of a *fixed-price contract* in which the loan officer's referral payment is fixed as a function of a borrower's performance in the graduation portfolio. Otherwise, the optimal referral contract takes the form of a *revenue-sharing contract*, in which the loan officer's compensation for a referral is increasing in the borrower's performance in the graduation portfolio.

The intuition for this result is that when the microcredit officer is intrinsically motivated, they internalize some of the efficiency loss of keeping high-type borrowers and from referring low-type borrowers. Hence, there may exist a fixed-price contract that induces them to make efficient referrals. As fixed-price contracts induce no distortion in the effort of graduation loan officers, when such contracts induce efficient referrals, they are optimal.

In contrast, when microcredit officers have low intrinsic motivation, a fixed-price contract cannot induce them to refer high-type borrowers without also inducing them to refer low-type borrowers, as even the microcredit officers generate more revenue from high-type borrowers. In such circumstances, revenue sharing is necessary to generate a wedge between the microcredit officer's payment for referring high- and low-type borrowers, and the firm must then accept some distortion in the graduation loan officer's effort to induce informative referrals.

We test the model's predictions through an experiment with our partner lender, spanning 241 loan officers and nearly 47,000 borrowers, in which we evaluated two referral compensation contracts: a fixed-price contract and a revenue-sharing contract. In the fixed-price contract, loan officers who referred a borrower were given a transfer equal to six-months of the compensation they would have derived from keeping the borrower in their portfolio. While the resulting compensation varied across borrowers as a function of their previous loan sizes and repayment rates, compensation was fixed as a function of borrower's performance in the graduation portfolio. The revenue-sharing contract provided an additional reward for loan officers that was increasing as a function of the performance of their referred borrowers in the graduation portfolio. Both contracts were evaluated relative to a baseline in which no explicit compensation was given for referrals. We utilize administrative data from several surveys – implemented by our partner lender – eliciting referrals from loan officers for borrowers who may be qualified for graduation loans. These referrals were high stakes in that our partner lender incorporated them into their ordinary operations and utilized them for graduation decisions. Though to preserve the fidelity of the study, referrals were not used until a year after our study began.

All loan officers received the compensation changes at the same time. Therefore, rather than randomizing the assignment of compensation contracts to loan officers, our experimental variation comes from randomizing the timing of surveys relative to the compensation changes. Specifically, our control loan officers received the referral survey five days before anyone found out about the compensation change, and therefore their referrals were influenced by the baseline contract. Our treatment loan officers received their referral survey two days following the announcement of the fixed-price compensation change. As we demonstrate in our analysis, it is extremely unlikely that the one week between the two surveys was sufficient time for loan officers to gather new information about their borrowers. Hence, any difference in the referrals between our treatment and control loan officers can be attributed to the compensation change. One month after the fixed-price contract was announced, all loan officers received news of a second change to their compensation contract – the revenue-sharing contract, followed by a final round of referral surveys.[1]

Our experiment confirms that pecuniary penalties for losing borrowers are a substantial deterrent to loan officer referrals. Indeed, the compensation changes resulted in several hundred new referrals for borrowers to graduate. These represent a 12% increase in referrals relative to those that were collected at baseline, and a far larger increase, in percentage terms, relative to those that our partner organization collected prior to our study.

The most important standard by which to evaluate the compensation changes, however, is not the number of additional referrals but rather the value of the additional referrals in predicting borrower repayment behavior and business growth. Graduated borrowers referred after the compensation shifts exhibit less than half as much default as graduated borrowers referred prior to the compensation shifts. Moreover, graduated borrowers referred after the shifts experience about twice as much growth in their profits relative to borrowers referred prior to the shift. Our results suggest that, prior to the compensation shift, not only were loan officers strategically withholding referrals of qualified borrowers, they were withholding referrals of their *most* qualified borrowers. Indeed, borrowers referred after the compensation shift also exhibited better repayment in the microcredit portfolio, which is consistent with the core mechanism of our model.

Beyond demonstrating that fixed-price and revenue-sharing contracts improve referrals and organizational performance, our empirical analysis confirms two other testable predictions of the model. Specifically, our model offers guidance on how to identify intrinsic motivation and predicts that intrinsically motivated loan officers should furnish better referrals than loan officers with less intrinsic motivation under any fixed-price contract. It also predicts that a revenue-sharing contract should improve the quality of referrals, and more-so for loan officers with low intrinsic motivation. These two predictions echo the general intuition that fixed-price contracts perform better for intrinsically motivated loan officers and revenue-sharing contracts perform better for non-intrinsically motivated loan officers. Our analysis confirms both predictions. Specifically, under the fixed-price contract, the referrals of intrinsically motivated loan officers predict about 5 percentage points less default, while those of non-intrinsically motivated loan officers are uncorrelated with default. Under the revenue-sharing contract, the referrals of non-intrinsically motivated loan officers improve, predicting about a 3 percentage point decrease in de-

[1] Due to logistical constraints we did not randomize the timing of surveys around the revenue-sharing announcement. However we argue in our analysis that even the one month between the announcement of fixed-price and revenue-sharing contracts is unlikely to be sufficient time for loan officers to gather meaningfully more information about their borrowers.

fault, while those of intrinsically motivated loan officers improve significantly less.

How broadly do our results generalize to other microfinance institutions? First, using data from MIX Market, we establish that over half of microfinance institutions worldwide have graduation programs, and a large majority compensate their loan officers for the size and repayment rate of their portfolio.[2] While these are necessary ingredients for our results to generalize, they are not sufficient. To develop a more granular view, we conducted a survey of managers at 46 microfinance institutions in Latin America, India, the Middle East and North Africa to assess their loan officer compensation practices. Of these institutions, 67% have internal graduation programs. 48% of those with graduation programs are similar to our partner lender at the time of our study in that distinct loan officers manage each type of loan, loan officers are compensated based on the size and quality of their portfolio, and microcredit loan officers are given no special bonus when borrowers graduate out of their portfolio to larger loans within the same institution. That is, the same factors that induced a misalignment of interests between loan officers and their borrowers are present in many other microfinance institutions around the world. Therefore, our experimental results suggest that loan officer compensation schemes may bear partial responsibility for limiting the impact that microcredit has had on entrepreneurship and more broadly on borrower incomes (e.g. Banerjee et al., 2015; Meager, 2019).

Our theoretical framework offers guidance for how our results generalize to organizations beyond microfinance institutions. Specifically, our model might generalize to any organization that relies on internal referrals, such as those discussed at the outset of this introduction. For any of those organizations, our model and empirical results suggest that in settings where referring agents are intrinsically motivated, a fixed-price contract may be optimal, while in settings where intrinsic motivation is low, organizations must rely on revenue sharing. We discuss this at more length in Section 7.

Our analysis contributes to several literatures. First is the empirical literature examining the consequences of incentive variation in firms (e.g. Baker, 1992; Shearer, 2004; Bandiera et al., 2007, 2009, 2010, 2013). Of special relevance are the studies that explore incentive provision in organizations with a social mission (for theory, see Bénabou and Tirole, 2006; Besley and Ghatak, 2005, 2018). This literature primarily focuses on the process of selecting intrinsically motivated workers and inducing their effort (e.g. Ashraf et al., 2014, 2019; Berg et al., 2019; Desarranno, 2019; Bandiera et al., 2023). Relative to the bulk of this liter-

[2] The MIX Market data were collected annually from 2002 to 2017, surveying the management practices of over 3100 MFIs around the world.

ature, our paper is distinct in that we isolate a strategic communication problem. Rather than the question of how to motivate employees to exert the optimal level of effort, our context is one in which our partner organization wanted to elicit information already held by its loan officers. In fact, our experimental design nearly ensures that loan officers could not exert effort to collect additional information about their borrowers, thereby isolating the strategic communication problem.

In this sense our paper complements Atkin et al. (2017), which argues that technology adoption is low amongst a set of Pakistani soccer-ball producers because of a strategic incentive of employees not to disclose the quality of the technology to their manager. The authors document a strategic communication problem by paying employees to demonstrate the quality of the technology to their manager, and they find that managers are more likely to implement the new technology after the demonstration. Relative to Atkin et al. (2017) we employ a more direct test of strategic communication and provide a richer description of its determinants.

We also contribute to the growing empirical literature on incentive provision in multilayered organizations (e.g. Bandiera et al., 2021; Deserranno et al., 2022), which goes beyond the analysis of a single principal supervising a set of symmetric agents. Much of this literature has focused on vertical hierarchies where a principal supervises several layers of subordinate agents. In contrast, we study an organization where a principal must supervise agents from two horizontally differentiated divisions and appropriately allocate incentives among them.

Finally, our paper contributes to the literature examining the decision process of loan officers and other lending agents within banks and microfinance institutions (e.g. Hertzberg et al., 2010; Cole et al., 2014; Fisman et al., 2017, 2018; Maitra et al., 2017; Agarwal and Ben-David, 2018; Vera-Cossio, 2021; Maitra et al., 2021). Most closely related are Karlan et al. (2018) and Giné et al. (2017), both of which document unintended consequences of incentive provision in microcredit institutions. In contrast to these papers, we evaluate the importance of a compensation scheme widely utilized by microfinance institutions, and we demonstrate that it leads to a substantial misalignment in the interests of loan officers and their borrowers. And our paper is distinct within this literature in focusing on loan officers' incentives to prevent borrowers from leaving their portfolios.

The remainder of our paper is organized as follows. Section 2 describes our context and outlines our theoretical framework and predictions. Section 3 describes the experimental design and data. Section 4 documents that loan officers were withholding referrals of qualified borrowers prior to our intervention. Section 5 demonstrates that borrowers referred after the compensation change exhibited better repayment in graduation loans and experienced more growth in business profits following graduation than those referred prior to the compensation change, indicating that loan officers had been withholding their most qualified borrowers prior to the compensation change. Section 6 provides support for the framework's testable predictions. Section 7 presents results from our novel survey of microcredit managers around the world, establishing broader applicability of our results, and Section 8 concludes.

2 Context and Theoretical Framework

We begin with background on our empirical context. We then outline the theoretical framework in general terms, with references to the empirical setting.

Our study was conducted in collaboration with one of Chile's largest microfinance institutions, which services more than 120,000 borrowers across the country. Their primary product is a joint-liability microloan. Borrowers who are geographically proximate are divided into groups of about 22 people.

The mean microloan size is USD 860, the typical duration of a loan cycle is 4.3 months, and repayments are made on a weekly or biweekly basis. Borrowers who successfully repay a loan are subsequently offered a larger one, up to a maximum of about USD 1300. Groups are held jointly liable for the loans of their members, such that no borrower can renew his or her loan if another group member defaults.

While microloans constitute the majority of our partner's portfolio, they also offer a *graduation loan* product. Graduation loans are larger than the microloans, averaging 3,625 USD, are individual liability, have an average duration of 17.5 months, and are repaid on a monthly basis. Borrowers cannot simultaneously hold a standard microloan and a graduation loan. As of 2019, graduation loans constituted 6.6% of our partner lender's portfolio in terms of assets under management.

One important feature of our partner lender is that, at the time of the study, the two loan products were housed in separate parts of the organization, supervised by different managerial hierarchies.[3] The loan officers who managed the microloans were entirely non-

[3]Microcredit loan officers reported to a branch manager, who was located in the same office as the loan officers. While graduation loan officers were stationed at branch offices alongside their microcredit loan officer colleagues, they reported directly to a manager at the head office.

overlapping with the loan officers who managed the graduation loans. Microcredit loan officers' day to day responsibilities included identifying new borrowers for their portfolio, holding biweekly meetings with joint-liability groups to ensure timely repayment, providing business and social trainings to their borrowers, determining loan sizes for repeat borrowers, and identifying candidates for graduation loans. We further describe microcredit loan officers in Section 3. In contrast, graduation loan officers' jobs placed much more emphasis on evaluating business plans and cash flows and monitoring the usage and progress of a loan after disbursal.

Graduation loan officers had several mechanisms to identify borrowers for the graduation portfolio. First, microcredit loan officers were encouraged to make referrals from their own portfolio based on the soft information they had about which borrowers seemed suitable for graduation. Second, graduation loan officers would conduct marketing campaigns in the joint-liability microcredit groups from which they would receive inbound applications. Finally, graduation loan officers would receive suggestions from the head office as to which borrowers were likely qualified to graduate based on their borrowing history.[4] The referral process from microcredit loan officers to graduation loan officers had been largely informal, and microcredit loan officers had not been forthcoming with referrals. Management hypothesized that microcredit loan officers' compensation was largely to blame for their lack of referrals.

Critically, at the time of our study, microcredit loan officers received a performance bonus based on the number of borrowers in their own portfolio and their portfolio default rate. The average performance bonus amounted to about 25% of loan officer compensation, or about USD 330 per month. Moreover, when the number of borrowers in any of their groups fell below 18, microcredit loan officers were responsible for replacing lost members by the following loan cycle. Each of these features of their compensation induced penalties on microcredit loan officers when they lost good borrowers—regardless of whether these borrowers were to leave the organization altogether or merely to graduate to graduation loans. And, at the time of our study, microcredit loan officers were not given any reward for helping qualified borrowers to graduate out of microcredit. We provide a complete description of the compensation scheme employed by our partner lender prior to our intervention in Online Appendix Section C.

The goal of our experiment was to identify candidate contracts that would induce mi-

[4] Regardless of whether an applicant was referred to the graduation portfolio by a microcredit loan officer, the graduation loan officer would screen inbound applicants utilizing their credit history, business plan, and a visit to the applicant's business.

crocredit loan officers to make good referrals to the graduation loan officers. In the experiment our partner lender first systematized the process of soliciting referrals and then introduced and evaluated the impact of two novel compensation schemes on the quantity and quality of loan officer referrals. Before describing the experiment, we turn to a theoretical framework to formally analyze the referral problem and identify candidate compensation schemes. This framework will motivate our experiment and guide our empirical analysis.

2.1 Model Setup

We adapt the model of Garicano and Santos (2004) of referrals within a partnership. To match our empirical setting, we will frame the model in terms of a lender who employs loan officers and serves borrowers, but the model could also represent other firms where employees must sometimes refer tasks to one another.

There are two agents (loan officers) $i \in \{l, h\}$. Agent l has low skill, represented by η_l and agent h has high skill, represented by η_h, with $\eta_l < \eta_h$. Without loss of generality, we assume $\eta_h = 1$. In our setting, the "low-skill" loan officer maps to the microcredit loan officer and the "high-skill" loan officer maps to the graduation loan officer who manages larger loans.[5]

We assume that the low-skill agent receives a client (borrower) of type $v_j \in \{v_0, v_1\}$, with $v_0 < v_1$, whose type is privately observed by the low-skill agent. The value v_i could be interpreted as the difficulty, or value, of the client's case. In our setting, a borrower of value v_1 is one that is suitable for a graduation loan, whereas a borrower with type v_0 is not. The low-skill agent must then decide whether to service the client themself, or refer the client to the high-skill agent.[6] If the client is referred to the high-skill agent, we assume the high-skill agent does not observe the client's quality, though this could be substituted by the weaker assumption that the low-skill agent observes some component of quality not observed by the high-skill agent. In our setting, this represents the fact that to be eligible to graduate from the microcredit portfolio, borrowers must have spent several loan cycles with their microcredit loan officer. Hence, their microcredit loan officer has

[5]High and low skill are metaphors that we adopt from Garicano and Santos (2004), but it may be more appropriate to think of the two types of loan officers as horizontally differentiated, specializing in different types of borrowers, rather than being vertically differentiated on skill.

[6]In our empirical context, when a microcredit loan officer refers a borrower to the graduation portfolio, it increases the likelihood that the borrower graduates but does not guarantee it. For simplicity, we assume in our model that a referral guarantees graduation, though the results would proceed similarly if referrals merely increased the likelihood of graduation.

ample time to collect private information about a borrower's quality prior to any referral decision.

Whichever agent j services the client, they must choose an effort $e \in \mathbb{R}^+$, thereby producing output $y = \eta_i v_j e$ at cost $\psi(e)$, with $\psi' > 0$ and $\psi'' > 0$. Therefore the agent's skill level and the client's type are complements. Either agent can opt not to service the client, instead enjoying an outside option utility $\bar{u}_i$. This outside option reflects either the value of the agent's leisure time, or the value of the other (unmodeled) tasks they may perform at the firm.

We assume that

$$\max_e \{\eta_l e v_0 - \psi(e)\} + \bar{u}_h > \max_e \{e v_0 - \psi(e)\} + \bar{u}_l$$

$$\max_e \{\eta_l e v_1 - \psi(e)\} + \bar{u}_h < \max_e \{e v_1 - \psi(e)\} + \bar{u}_l$$

and

$$\max_e \{\eta_l e v_0 - \psi(e)\} > \bar{u}_l$$

so that it is efficient for the high- (low-) skill agent to service the (low-) high- value opportunity, and so that the low-skill agent would prefer to draw opportunities rather than enjoy their outside option. We note that while it is efficient for the high-skill agent to serve the high-value opportunity, both agents can generate more revenue from the high-value opportunity than the low-value one.

In our principal departure from Garicano and Santos (2004), we assume that agents are intrinsically motivated, internalizing not only their income and effort costs, but also partially internalizing social welfare. Specifically, agent i's payoff is

$$I_i(v, e_i) - \psi(e_i) + \theta_i W(v, e_j, j)$$

where $I_i(v, e)$ is the income of agent i when the low-skill agent receives a client of type v (potentially referring it to the high-skill agent), and

$$W(v, e_j, j) = \begin{cases} \eta_l e_l v - \psi(e_l) + \bar{u}_h & \text{if } j = l \\ e_h v - \psi(e_h) + \bar{u}_l & \text{if } j = h \end{cases}$$

is the social welfare generated when an opportunity v is assigned to agent j who exerts effort e_j. For expositional simplicity we assume that $\theta_h = 0$ for the high-skill agent h, so that the high-skill agent is not intrinsically motivated, and our main comparative static of interest is the degree of intrinsic motivation θ_i of the low-skill agent i. As we show in the appendix, our results would be unchanged by assuming that the high-skill agent was also intrinsically motivated. When $\theta = 0$ this model reduces to that of Garicano and Santos (2004).

The firm chooses a referral contract to maximize its output less the cost of labor, subject to constraints. For simplicity we restrict attention to linear referral contracts. Specifically, we consider referral contracts of the form $p + sy$ for $p \in \mathbb{R}^+$ and $s \in [0, 1]$, which dictate that when the low-skill agent refers a client and the total output is y, they receive a payment of $p + sy$ and the high-skill agent receives the residual: $(1 - s)\, y - p$. We assume that when the low-skill agent keeps the opportunity, they retain the full output and the high-skill agent enjoys their outside option.

Our results hold in more general contracting spaces, but do require the assumption of budget-balance, whereby the full output y is divided between the payments to the two agents. This assumption implies that the larger is the compensation of the low-skill agent in a given state of the world, the smaller must be the compensation of the high-skill agent. The constraint literally implies that the firm cannot generate profits (i.e. its revenues match its wage bill), and hence is a good match for non-profit firms. Indeed, this is the organizational form of our partner lender. There are several alternative situations where this assumption holds. Garicano and Santos (2004) justifies the assumption by alluding to ex-post efficiency, which may best match situations where the two agents are also the firms' owners. Budget-balance would also hold in highly competitive markets, where free entry drives firm profits to zero. Finally our results would hold in an environment where holding output fixed, the more a firm pays to one agent, the costlier it is on the margin to compensate the other agent. One such environment would where a firm owner – who is the residual claimant on firm profits – has concave utility.

Conditional on the low-skill agent receiving the high-value opportunity, the firm's optimization problem is to maximize efficiency:

$$\max_{\{\text{Refer,Keep}\}} \left\{ \max_{p,s,y_h(v_1|v_1)} y_h\left(v_1|v_1\right) - \psi\left(\frac{y_h\left(v_1|v_1\right)}{v_1}\right) - \bar{u}_h, \max_{y} y - \psi\left(\frac{y}{\eta_l v_1}\right) - \bar{u}_l \right\}$$

such that

$$\max_{y}\left\{y-\psi\left(\frac{y}{\eta_l v_0}\right)+\theta W\left(v_0,\frac{y}{\eta_l v_0},l\right)\right\}\geq \bar{u}_l+p+sy_h\left(v_0|v_1\right)+\theta W\left(v_0,\frac{y_h\left(v_1|v_1\right)}{v_1},h\right) \quad (1)$$

$$y_h\left(v_1|v_1\right)=\underset{y}{\text{argmax}}\left(1-s\right)y-p-\psi\left(\frac{y}{v_1}\right) \quad (2)$$

$$\left(1-s\right)y_h\left(v_1|v_1\right)-p-\psi\left(\frac{y_h\left(v_1|v_1\right)}{v_1}\right)\geq \bar{u}_h \quad (3)$$

Here, $y_h\left(v_1|v_1\right)$ is the prescribed output when the high-skill agent receives the high value opportunity, $y_h\left(v_0|v_1\right)=y_h\left(v_1|v_1\right)\frac{v_0}{v_1}$ is the amount of output produced when the high-skill agent believes they have received the high-value case but has in fact received the low-value case, and s and p are the parameters of the referral contract described above.

The first argument in the maximization problem is the firm's output $y_h\left(v_1|v_1\right)$ minus the cost of labor $\psi\left(\frac{y_h(v_1|v_1)}{v_1}\right)-\bar{u}_h$ conditional on referring a high value case. The second argument is analogous for the case where the high value case is kept by the low-skill agent.

Inequality 1 is the low-skill agent's incentive compatibility constraint dictating that they should not refer low-value cases, inequality 2 is the high-skill agent's incentive compatibility constraint dictating that $y_h\left(v_1|v_1\right)$ should maximize their payoff given their share of the output $\left(1-s\right)y-p$, and inequality 3 is the high-skill agent's individual rationality constraint.

Finally, when the above program selects the first argument in the maximization problem, we will need to verify that it is incentive compatible for the low-skill agent to refer their case, i.e.

$$sy_h\left(v_1|v_1\right)+p+\bar{u}_l+\theta W\left(v_1,\frac{y_h\left(v_1|v_1\right)}{v_1},h\right)\geq \max_{y} y-\psi\left(\frac{y}{\eta_l v_1}\right)+\theta W\left(v_1,\frac{y}{\eta_l v_1},l\right) \quad (4)$$

The low-skill agent's individual rationality constraint is trivially satisfied in either case.

2.2 Model Analysis

The core tension in this model comes from the interplay of the low-skill agent's referral incentive compatibility constraint 1 and the high-skill agent's effort incentive compatibility constraint 2. Conditional on receiving the high-value case, the high-skill agent exerts efficient effort when they retain the full value of their marginal output, i.e. when $s = 0$. The lower their share of the marginal output, the larger is the distortion from efficient effort. On the other hand, social efficiency requires that the low-skill agent refers high-value, but not low-value cases. The larger is the low-skill agent's revenue share s, the larger is the difference between their payoff when they refer the high- versus low-value case. Hence, budget balance induces a tradeoff between the strength of incentives for the high-skill agent's effort and the low-skill agent's referrals. Garicano and Santos (2004) demonstrates that when $\theta = 0$ (i.e. agents are not intrinsically motivated) the optimal contract induces a departure both from efficient referrals and from efficient effort. When $\theta > 0$, we demonstrate that this compromise may no longer be necessary.

When $s = 0$ and $p > 0$ we say there is a *fixed-price contract* . When $s > 0$ we say there is *revenue-sharing contract.* Our main result is the following.

Proposition 1. *There exists a $\bar{\theta}$ such that for $\theta \geq \bar{\theta}$, a fixed-price contract is optimal, and for $\theta < \bar{\theta}$, a revenue-sharing contract is optimal.*

Formal proofs are relegated to the appendix. To see the first part of this result, note that the higher is the low-skill agent's intrinsic motivation θ, the more they internalize the welfare benefit of keeping low-value opportunities and referring high-value opportunities. For a fixed-price contract to induce efficient referrals, it must be that these welfare benefits outweigh the difference in revenue that the low-skill agent derives from high- versus low-value opportunities when she retains them both. Clearly, this is satisfied for agents with θ greater than some $\bar{\theta}$. In this case, the optimal contract attains first-best, inducing efficient referrals and efficient effort, as the high-skill agent retains the full marginal value of their effort.

For agents with lower θ, any fixed-price contract that induces them to refer the high-value cases would also induce them to refer the low-value cases. Then, to induce a separating equilibrium, a formalization of the discussion preceding Proposition 1 implies that a revenue-sharing contract is optimal, which induces a deviation both from efficient referrals and from efficient effort.

This motivates the two interventions described in the following section, the first of which is a fixed-price contract and the second of which is a revenue-sharing contract. Our interventions take the same structure as the optimal compensation scheme (with high and low degrees of intrinsic motivation), but we do not claim them to be optimally calibrated.

We next modify the model by introducing an idiosyncratic cost that the low-skill agent faces in servicing a case. We introduce this feature to better map to our empirical setting and derive additional testable predictions. We show in the appendix that Proposition 1 continues to hold under this modification. Both of the testable predictions arise from and enrich the intuition that fixed-price contracts perform better for intrinsically motivated agents, and revenue-sharing contracts perform better for non-intrinsically motivated agents. These predictions leverage the fact that we phased in the two contracts, first implementing a fixed-price contract and then a revenue-sharing contract.

We assume that when the low-skill agent draws a case, they realize an idiosyncratic fixed cost $\varepsilon \sim F$ of servicing the client, for some probability distribution F with bounded support.

Now consider any fixed-price contract p. The low-skill agent refers a low-quality case if and only if

$$\max_y y - \psi\left(\frac{y}{\eta_l v_0}\right) + \theta W\left(v_0, \frac{y}{\eta_l v_0}, l\right) - \varepsilon \leq p + \bar{u}_l + \theta W\left(v_0, \frac{y_h\left(v_0|v_1\right)}{v_1}, h\right)$$

It is straightforward to verify that the probability the low-skill agent refers the low-quality case is decreasing in θ.

Similarly the high-quality case is referred if and only if

$$p + \bar{u}_l + \theta W\left(v_1, \frac{y_h(v_1|v_1)}{v_1}, h\right) \geq \max_y y - \psi\left(\frac{y}{\eta_l v_1}\right) + \theta W\left(v_1, \frac{y}{\eta_l v_1}, l\right) - \varepsilon$$

So the probability the low-skill agent refers the high quality opportunity is increasing in θ.

Therefore we have the following prediction.

Proposition 2. *The quality of referrals furnished in a fixed-price contract is increasing in the low-skill agent's intrinsic motivation θ.*

Next, following the design of our experiment, suppose a firm were first to elicit referrals under a fixed-price contract p, and then were to implement a revenue-sharing contract $p + sy$ and elicit a subsequent batch of referrals (non-overlapping with those from the first batch). Suppose further that $sy(v_0|v_1) < 0$ – i.e. the firm loses money on bad referrals and the revenue sharing component of the payoff for referring a low quality case is negative. Then we have the following prediction.

Proposition 3. *For agents with low intrinsic motivation, the quality of referrals in the revenue-sharing contract is higher than in the fixed-price contract. For agents with high intrinsic motivation, the corresponding increase in referral quality is smaller.*

The revenue-sharing contract induces referrals for only high-quality opportunities, as relative to the earlier fixed-price contract, the benefit (cost) of referring high- (low-)quality opportunities has increased. In the fixed-price contract, agents of every level of intrinsic motivation have a positive probability of referring low-quality opportunities, but this is more likely for low-intrinsic motivation agents. Hence the improvement in referral quality between the fixed-price and revenue-sharing contracts is most pronounced for agents with low intrinsic motivation.

In summary, when agents are intrinsically motivated, fixed-price contracts induce efficient referrals without distorting the incentives of the high-skill agent. When agents are not intrinsically motivated, Proposition 2 implies that fixed price contracts are ineffective. In this case, Proposition 3 implies that revenue-sharing contracts perform better. We note that these predictions hold for all fixed-price and revenue-sharing contracts, and hence do not require them to be optimally calibrated. We further note that our model does not make a prediction about how the performance of the high-skill agent changes with the introduction of a revenue-sharing contract. This is because their incentive to exert effort diminishes, but the quality of the referrals they receive from low-skill agents also increases.

Finally, the model offers guidance for inferring the intrinsic motivation θ of an agent.

Proposition 4. *When agents are provided no compensation for referrals, the quality of their referrals is increasing in θ.*

As we describe below, our data include a round of referrals elicited prior to the implementation of any referral contract. We will use the quality of referrals in this round as a proxy for intrinsic motivation.

3 Experimental Design and Data

Motivated by the above analysis, we experimentally evaluated two referral compensation schemes: a fixed-price contract and a revenue-sharing contract. Each of these provided explicit incentives for microcredit loan officers to refer borrowers to the graduation portfolio. Due to organizational constraints, we were not able to induce individual variation in loan officer compensation; each of our two compensation schemes was rolled out to all loan officers at the same time. Our experimental variation comes from the timing of surveys relative to the announcement of the compensation change. Namely, our control loan officers were surveyed five days prior to their discovery that their compensation scheme would be adjusted and our treatment loan officers were surveyed two days following the communication of this information. Both of the compensation changes described below were a surprise to all loan officers, revealed only on the day of their implementation. Figure 1 presents a timeline of the compensation changes and surveys.

This experimental design may prove useful for other research inside firms in situations where managers are reluctant to treat employees differently from one another. This design could be applied in any setting in which measures of output are obtainable in close temporal proximity to a policy change.[7]

Modifications of Referral Process Prior to Novel Contracts. An important element of our study is that we helped to formalize the process of collecting referrals *prior to the introduction of novel referral contracts*. The referral surveys were the product of a collaboration between the research team and the partner lender, but were presented to loan officers as part of the ordinary course of business. Specifically, management highlighted the importance of referrals to the organization, and that the process of collecting referrals was being formalized and streamlined, but that referrals would be used as inputs into the graduation process in the same manner as they had been previously.[8] In Online Appendix A we include the initial communication from headquarters to branch managers introducing the novel survey instrument (Figure A1), as well as an example of the survey

[7]Examining measures of organizational output before and after a change of management practices has a long history in organizational economics. For instance, Lazear (2000) examines the change in worker productivity after a switch from hourly wages to piece rates in a large manufacturing firm. Relative to Lazear (2000), our research design has two important advantages. First, our key output variable–referrals–can be measured immediately before and after the organizational change, rather than over weeks or months. So time trends are less likely to confound the results in our setting. Second, we *randomized* whether referrals were elicited right before or right after the organizational change. The initial elicitation of referrals may itself influence the subsequent reporting of referrals (i.e. a loan officer being asked for a second time for referrals may report more or fewer than a loan officer being asked her first time, all other things equal), and randomization ensures that we can compare loan officer referrals among those who have been asked the same number of times, under different compensation schemes.

[8]This was indeed the case, though as part of our research protocol referrals were withheld from graduation loan officers for one year, until we had enough data to judge the value of referrals in predicting borrower repayment behavior. Nevertheless, some referred borrowers graduated in the intervening year (having applied for the graduation loan and received one independently from their referrals), so payments from the two referral contracts took place in the study's first year.

instrument (Figure A2). Loan officers were provided a form with all of their borrowers (organized by joint-liability group) and asked (a) to refer borrowers who are suitable for graduation and (b) a strength of the referral on a scale of 1–5.

That the process of referrals was systematized and that loan officers were explicitly reminded of the importance of referrals prior to any compensation change is an important part of our study design. This ensures that the introduction of the new contracts is not confounded with the impacts of referral formalization and signaling of firm priorities.

Referral Contracts. With our guidance, in March of 2019 our partner lender announced the first change in the compensation scheme for microcredit loan officers. The new compensation scheme, which we refer to as the *fixed-price contract*, provided a transfer to microcredit loan officers who referred borrowers that subsequently moved to the graduation portfolio. This transfer was equal to six months of the referred borrower's contribution to the microcredit loan officer's variable compensation. Specifically, under the new incentive scheme, loan officers were given a six month grace period for each graduated borrower, during which graduated borrowers continued to be treated as part of the loan officer's portfolio for the purpose of calculating their bonus.[9] Critically, this transfer was fixed as a function of borrowers' repayment behavior in the subsequent graduation loan (i.e. $s = 0$ in the notation of the previous section), consistent with the fixed-price contract of Proposition 1. The average compensation for a referral was about USD 6, which represents about 0.5% of a loan officer's average compensation. In addition to the monetary transfer, loan officers were given an additional cycle to replace lost borrowers for groups that fell below the minimum size of 18.

In April of 2019 our partner organization announced the second, and final change to loan officer compensation, which we refer to as the *revenue-sharing contract*. In the revenue-sharing contract, in addition to maintaining the features of the fixed-price contract, loan officers were rewarded for referring borrowers that subsequently went on to receive graduation loans and exhibit good repayment behavior, and penalized for those that exhibited bad behavior. The new rewards and penalties only applied to referrals made after the announcement of the revenue-sharing contract. Rewards were calculated as a function of *points* a loan officer earned—for each borrower that was referred and subsequently graduated, loan officers gained three points if the borrower exhibited good repayment behavior in the first three months of the graduation loan and conversely they lost one point for re-

[9] Recall, the details of this bonus calculation are in Online Appendix Section C.

ferred borrowers who exhibited poor repayment in the first three months. Points could be exchanged for various rewards. To give an approximate sense of the value of a point, three points could be exchanged for a day off, or one point could be exchanged for a sleeping bag, or a pair of Bluetooth headphones among many other things. Critically, the revenue-sharing contract induced a payment that was an increasing function of the borrower's performance in the graduation portfolio (i.e. $s > 0$ in the notation of the previous section), consistent with the fixed-price contract of Proposition 1.[10]

Given the theory in Section 2, it is worth considering why our partner lender had no referral contract in place prior to this study. We believe there are two primary reasons. First, like many microfinance institutions with a graduation program, our partner lender only began to develop its graduation loan product after establishing a successful traditional microcredit business. Thus, its original incentive policies were optimized for a microcredit-only business. Various frictions make it difficult to change compensation policies once they are in place. Second, the theory in Section 2 indicates that if loan officers are sufficiently intrinsically motivated, having no referral contract at all is optimal. Given these considerations, our partner lender was only willing to revise their compensation policies in conjunction with a study to evaluate if their benefit outweighed the cost of transition.

Surveys, Data, and Timeline. As described in Figure 1, we utilize four rounds of surveys to collect referrals from microcredit loan officers about which borrowers would be suitable for graduation.[11] The first survey round was our baseline ($Baseline$), which occurred in November 2018 and during which all loan officers were surveyed. At this point the firm's management set the explicit expectation that loan officers would be periodically resurveyed to update their referrals.

The second ($Pre\text{-}Fixed\text{-}Price$) occurred five days before the announcement of the fixed-price contract in March 2019. We randomly selected half of the microcredit loan officers – our control group – to be surveyed at the $Pre\text{-}Fixed\text{-}Price$ round, during which they were given the opportunity to update the referrals they provided at baseline. All referral surveys were conducted during a weekly branch-wide loan officer meeting. At the $Pre\text{-}Fixed\text{-}Price$ survey wave, all loan officers were told they would be asked to update

[10] While budget balance would imply that implementing the revenue-sharing scheme would also require muting the graduation loan officer's incentive for recovery, our partner lender was willing to incur a small deficit for the duration of the study and hence did not alter the graduation loan officer's incentives. We discuss their long-term solution to this problem in the conclusion.

[11] As these referral surveys were integrated into the firm's ordinary processes, they a form of administrative data. Nevertheless, going forward we will refer to them as surveys.

their referrals, but due to (legitimate) capacity constraints only half would update their referrals during that meeting and the other half would be asked to update their referrals in the meeting the following week.

The third survey ($Fixed\text{-}Price$) occurred one week after the $Pre\text{-}Fixed\text{-}Price$ survey, and two days after the compensation change. All loan officers were surveyed during the $Fixed\text{-}Price$ survey and given yet another opportunity to update their referrals.

Our primary comparison of interest is between the referrals collected by loan officers in the $Pre\text{-}Fixed\text{-}Price$ survey round, and the referrals collected from loan officers in the $Fixed\text{-}Price$ survey round *who were not also surveyed in the* $Pre\text{-}Fixed\text{-}Price$ *round.* As we discuss below, we attribute this difference to the treatment effect of changing the compensation scheme as only one week elapsed between the survey rounds and there was therefore little time for loan officers to collect new information. As a secondary estimate of the same treatment effect, we compare the referrals collected from loan officers in the $Pre\text{-}Fixed\text{-}Price$ survey round to the referrals collected from the same loan officers in the $Fixed\text{-}Price$ survey round. We make these comparisons precise in the following section.

Finally, in the week following the announcement of the revenue-sharing contract we utilize one final survey round ($Revenue\text{-}Sharing$), which collected referrals from loan officers. All microcredit loan officers were included in this survey. Because of logistical constraints, we did not randomize the timing of this survey relative to the introduction of the revenue-sharing contract. Roughly one month elapsed between the $Fixed\text{-}Price$ and $Revenue\text{-}Sharing$ surveys. In principle therefore the additional referrals collected after the revenue-sharing contract was implemented could be attributable to additional information that loan officers collected in the intervening month. However we present evidence below that very few of the additional referrals collected in the $Revenue\text{-}Sharing$ survey are due to the elapsed time, and that the great majority of these referrals are attributable to the compensation shift. Moreover, our partner lender did not implement any other policy changes in the intervening month, and we are not aware of any important public policy changes in Chile more broadly.

In addition to these surveys, our analysis draws on the administrative data of our partner lender. Specifically, our partner lender collects data on borrower demographic and business characteristics at the first and fourth loans. In 2020 our partner lender began updating select business characteristics, including profits, each time a borrower renewed their loan. And we utilize administrative data on loan officer portfolio characteristics and borrower repayment at the weekly level for microcredit loans and graduation loans.

Ethical Considerations. We now comment on the ethics of this experimental design. One concern is that we had knowledge of an impending compensation change that was not disclosed to loan officers when they furnished their initial batches of referrals. Had they known about these compensation changes ahead of time, they might have provided different referrals, and ultimately achieved a higher level of compensation – indeed this is the premise of our study.

There are several reasons we believe this was an ethical study. The fixed-price contract made it strictly more attractive to refer any given borrower. Hence, any loan officer who chose to withhold the referral of a borrower at the $Pre\text{-}Fixed\text{-}Price$ survey wave, because they believed that a referral was not in their financial interest, could rectify that decision in the $Fixed\text{-}Price$ survey wave, achieving the same level of compensation as if they had known about the fixed-price contract from the beginning of the study.

The revenue-sharing contract only took effect for referrals made after the contract was announced. Hence, in contrast to the fixed-price contract, it is possible that upon learning about the revenue-sharing contract, a loan officer could regret having made referrals of qualified borrowers prior to the announcement of the new contract. That is, a loan officer who wanted to maximize their financial gain and who had knowledge of the impending contract would wait to refer their good borrowers until after the announcement of the contract, so that they could accrue points for the full set of qualified borrowers that graduated from their portfolio.

Here we emphasize that limited liability ensured that no loan officer could be made worse off by the revenue-sharing contract relative to if it had never been implemented. And neither of these schemes would have been implemented in the absence of a study to evaluate their efficacy. Therefore, we believe this study was ethical, as all loan officers were made strictly better off as a result of this study relative to if it had never been implemented. Nevertheless, researchers who plan to implement similar experimental designs to evaluate compensation practices should take careful consideration of potential ethical concerns that might arise from the implementation of other contracts.

Descriptive Statistics and Experimental Balance. Our sample comprises all loan officers and microcredit borrowers at branches in which our partner lender offers graduation loans from October 2018 to February 2020. This represents 46,797 borrowers and 241 loan officers. Column 1 of Table A1 presents our balance check and sample descriptive statistics. The microcredit borrowers are on average 46 years old, 20% are male, 42% of them are married and 64% have completed secondary school. The most common business sector is retail, representing 58% of the sample, followed by 29% in manufacturing, and 12% is services. On average, businesses in our sample earn USD 704 per month in profits, and have on average 0.12 non-household workers. The average microcredit loan size is USD 899, and the average borrower has taken 8 loans from our partner organization.

The average microcredit loan officer in our sample has just over 340 borrowers in her portfolio and manages about USD 280,000 of loans. They are on average 38 years old. Approximately 36% have a university degree (although almost all loan officers have post-high school education) and 80% have a background in social work.[12] Their average tenure at our partner lender is 9.5 years. We note that although graduation loan officers are not a part of the study, their characteristics are very different from those of microcredit loan officers - nearly 70% of graduation loan officers have a university degree and, predominantly, have backgrounds in business or engineering.

Amongst loan officers who were randomly selected to refer borrowers before the fixed-price contract versus those who were not, the only statistically significant difference is that borrowers of loan officers surveyed after the fixed-price contract have slightly fewer non-household workers (significant at the 10% level). An F-test does not reject that the two groups are drawn from the same population.

4 The Impact of the Compensation Changes on the Quantity of Referrals

In this section we discuss the impact of the two compensation changes on loan officer willingness to refer borrowers for graduation.

The Impact of the Fixed-Price Contract

We use two primary regression specifications to evaluate the impact of the fixed-price contract on the number of referrals furnished by loan officers. Our preferred specification leverages between-subject variation comparing the number of referrals we received from loan officers who were surveyed just before the fixed-price contract was introduced to those who were *only* surveyed just afterwards. This is a comparison of groups A and C in

[12] In Chile, social work degrees are conferred not only by universities, but also technical and vocational schools.

Figure 2. Specifically we regress

$$y_i = \alpha + \beta_1 \mathit{Fixed\text{-}Price}_i + \gamma X_i + \mu_B + \epsilon_{it} \tag{5}$$

where y_i is the number of referrals furnished by loan officer i, $\mathit{Fixed\text{-}Price}_i$ is an indicator for whether loan officer i was only asked for referrals immediately following the introduction of the fixed-price contract, μ_B is a branch fixed effect, and X_i is a vector of loan officer controls: total referrals given by the loan officer at baseline, size of total loan portfolio in November 2018, and number of borrowers in the loan officer's portfolio in November 2018. We present heteroskedasticity robust standard errors. β_1 is the coefficient of interest, representing the difference between the number of referrals furnished by loan officers under the old incentive scheme and the number furnished by loan officers under the fixed-price contract.

Our second specification leverages within-subject variation and compares referrals from groups A and B in Figure 2. Specifically, for loan officers who were randomly selected to be surveyed both one week before and immediately after the introduction of the fixed-price contract, we regress

$$y_{it} = \alpha + \beta_1 \mathit{Fixed\text{-}Price}_{it} + \delta_i + \epsilon_{it} \tag{6}$$

where y_{it} is the cumulative number of referrals furnished by loan officer i in survey round t, δ_i is a loan officer fixed effect, and $\mathit{Fixed\text{-}Price}_{it}$ is an indicator for whether loan officer i was exposed to the fixed-price contract in survey round t. Standard errors are clustered at the loan officer level. Here β_1 represents the additional referrals furnished by loan officers after they were exposed to the fixed-price contract.

Finally, we combine these two sources of variation in a pooled regression specification on our full sample.

$$y_{it} = \alpha + \beta_1 \mathit{Fixed\text{-}Price}_{it} + \gamma X_i + \mu_B + \epsilon_{it} \tag{7}$$

We therefore pool across groups B and C in Figure 2 and compare their outcomes to the outcomes of group A, and standard errors are clustered at the loan officer level.

Across all of the above specifications, we estimate the regression models using data from our $\mathit{Pre\text{-}Fixed\text{-}Price}$ and $\mathit{Fixed\text{-}Price}$ survey waves.

Table 1 presents our estimates of the impact of the fixed-price contract on loan officer referrals. Columns 1 and 2 correspond to estimates of the between-subjects Specification 5, column 3 corresponds to the within-subjects Specification 6, and columns 4 and 5 correspond to the pooled Specification 7. When there are two columns for a specification, the second includes loan officer controls.

Across all specifications, loan officers affected by the fixed-price contract furnished between 1.1 [SE: 0.28] and 1.6 [SE: 0.53] additional referrals. This is not only statistically significant but also economically significant. Compared to the $Pre\text{-}Fixed\text{-}Price$ round, the loan officers surveyed in the $Fixed\text{-}Price$ round furnished more than 300 additional referrals. This is our first piece of experimental evidence that loan officers were strategically withholding referrals prior to our compensation shift.

Before assessing the impact of the revenue-sharing contract, we address a possible confound in our analysis of the impact of the fixed-price contract. Namely, one week elapsed between the $Pre\text{-}Fixed\text{-}Price$ survey and the $Fixed\text{-}Price$ survey. We attribute the difference in the number and quality of referrals between these survey waves to the introduction of the fixed-price contract, which occurred in the intervening week, but in principle other things could have changed as well. Certainly, our partner lender did not change or introduce any new policies during the week, and we are not aware of important public policy changes in Chile during the week. And we argue in the next section that one week was not enough time for loan officers to collect new information about their borrowers – indeed, 3 months elapsed between our baseline and $Pre\text{-}Fixed\text{-}Price$ survey without any intervening compensation changes, yet our $Pre\text{-}Fixed\text{-}Price$ survey produced almost no new referrals. So, time alone cannot account for this difference.

Could loan officers have communicated with one another in the intervening week in a manner that would influence our results?[13] We do not think this is a likely confound, as no loan officer had private information about any aspect of our study. In the $Pre\text{-}Fixed\text{-}Price$ survey round all loan officers, both those who were and were not surveyed, knew that an referral survey was taking place. And no loan officer knew of the impending compensation changes prior to them taking place. Nevertheless, it is theoretically possible that merely having experienced an additional referral survey caused the loan officers surveyed in the $Pre\text{-}Fixed\text{-}Price$ wave to communicate with their non-surveyed peers in a manner that caused the latter group to furnish additional referrals.

To rule out this possibility, we replicate the analysis in Table 1, with the inclusion of two additional controls to proxy for the extent to which loan officers are likely to communicate

[13]We thank Iwan Barankay for raising this possibility and for suggesting the tests we implement to address it.

with one another. For each loan officer i we control for the number of other loan officers that joined our partner lender in a six month window of loan officer i's start date. This is a proxy for how many friends the loan officer has and therefore the extent to which their responses in the $Fixed\text{-}Price$ survey could have been contaminated by communication. Second, we control for loan officer tenure, as loan officers who have been with the organization for a longer time are more familiar with it and less likely to be influenced by informal communication. We also include interaction terms between these variables and $Fixed\text{-}Price_{it}$. These results are presented in Table A2. The inclusion of these controls does not materially affect our estimates, and the novel interaction terms are small and not statistically significant. In sum, there is no evidence that communication between loan officers is an important confound of our results.

The Impact of the Revenue-Sharing Contract

Next we examine the impact of introducing the revenue-sharing contract. As discussed in Section 3, the revenue-sharing contract was introduced in April 2019 without random variation. Therefore to evaluate the impact of the revenue-sharing contract we estimate two regression models

$$y_{it} = \alpha + \beta_1 Fixed\text{-}Price_{it} + \beta_2 Revenue\text{-}Share_{it} + \gamma X_i + \delta_i + \epsilon_{it} \tag{8}$$

presented in columns 6 and 7 of Table 1, and

$$y_{it} = \alpha + \beta_1 Fixed\text{-}Price_{it} + \beta_2 Revenue\text{-}Share_{it} + \beta_3 Pre\text{-}Fixed\text{-}Price_{it} + \gamma X_i + \delta_i + \epsilon_{it} \tag{9}$$

presented in column 8 of Table 1.

In Specification 8 we include data from three of the four survey rounds: the $Pre\text{-}Fixed\text{-}Price$ survey wave immediately preceding the fixed-price contract, the $Fixed\text{-}Price$ survey wave immediately following fixed-price contract and the $Revenue\text{-}Share$ survey wave immediately following the revenue-sharing contract. The omitted group is the total number of referrals given during $Pre\text{-}Fixed\text{-}Price$. We exclude data from the $Baseline$ survey wave.

Specification 9 also includes data from the $Baseline$ survey wave, which serves as the omitted group. So we can separately estimate the number of referrals attributable to the

Pre-Fixed-Price survey wave. In both cases standard errors are clustered at the loan officer level.

Importantly, one month elapsed between the *Fixed-Price* survey and the *Revenue-Share* survey. Therefore, we may not be able to fully attribute all additional referrals reflected in β_2 to the impact of the revenue-sharing contract. Perhaps, even abstracting from our compensation changes, loan officers would anyways have accumulated new information in the elapsed month about borrowers who were qualified to graduate out of the microcredit portfolio. However, we note that between our baseline in November and our *Pre-Fixed-Price* survey in February, more than three months elapsed. Assuming that the number of additional referrals attributable to time is a linear function of time, the coefficient β_3 in Specification 9, corresponding to the additional referrals collected in our *Pre-Fixed-Price* survey, provides a conservative estimate of the number of additional referrals from the *Revenue-Share* round that can be attributed to the elapsed time. Hence, to the extent that β_2 is significantly larger than β_3, we can be confident that the revenue-sharing contract had an impact on loan officer willingness to refer their borrowers.

The estimates in Table 1 imply that loan officers furnished between 2.1 [SE: 0.34] and 2.4 [SE: 0.38] additional referrals as a result of the fixed-price and revenue-sharing contracts jointly. In contrast, our estimates of β_3 in column 8 demonstrates that loan officers only furnished an additional 0.12 [SE: 0.24] additional referrals in our *Pre-Fixed-Price* survey relative to *Baseline*, indicating that time trends do not account for the additional referrals collected in the *Revenue-Share* round. Together these comprise our second piece of experimental evidence that loan officers were strategically withholding referrals prior to the compensation shift.

Once again, we highlight that these results are not only statistically significant but they are also economically significant. Compared to the number of referrals collected at baseline, the additional referrals attributable to the changes in compensation amount to a roughly 12% increase. This in part reflects the efficacy with which referrals were collected at baseline. Prior to our study, our partner lender received few referrals from microcredit loan officers, so the additional referrals attributable to changes in compensation would amount to an enormous increase, in percentage terms, relative to the referrals collected prior to our study.

Finally, the strongest standard by which we can judge the impact of our compensation change is by the number of additional *valuable* referrals collected in each survey round. And as we will show in Section 5, the referrals collected after the compensation shift were far more valuable – both in terms of predicting loan performance and business growth – than those that were collected prior to the shift.

5 The Predictive Power of Referrals

Our next line of inquiry regards the value of referrals furnished across the various survey rounds in predicting the repayment behavior and business growth of borrowers. In this section we demonstrate that loan officer referrals are valuable in predicting the repayment behavior in the graduation portfolio (in the next section, we demonstrate that referrals are also predictive of repayment in the microcredit portfolio). We further demonstrate that referrals predict business growth following graduation loans. In each of these cases, referrals remain valuable even after controlling for observable characteristics. Hence loan officers have valuable soft information not easy to infer from borrower characteristics.

Importantly we find evidence that borrowers referred after the fixed-price and revenue-sharing contracts exhibit better repayment behavior and more business growth than borrowers referred at baseline. Hence, not only were loan officers impeding the graduation of qualified borrowers, but they were impeding the graduation of their *most qualified* borrowers.

The fact that borrowers referred after the fixed-price and revenue-sharing contracts have better performance in *both* portfolios represents an important misalignment between the interests of loan officers and those of our partner lender. Consistent with the framework of Section 2, these are the borrowers that our partner lender would like to graduate to larger loans, yet they are also the borrowers that loan officers would most like to keep in their portfolio. Our results indicate that this misalignment of interests is important in practice.

Referrals Predict Graduation Loan Performance

At the outset, we note that all graduated borrowers underwent a separate screening procedure managed by the set of loan officers who specialize in graduation loans. At the time of our study, we did not share the microcredit loan officer referrals with our partner lender.[14] Therefore, the graduation procedure was not informed by the referrals collected

[14] Recall, loan officers were told that their referrals would eventually inform the graduation process. This was indeed the case, though as part of our research protocol referrals were withheld from graduation loan officers for one year, until we had enough data to judge the value of referrals in predicting borrower repayment behavior.

in our survey. So this section can be understood as evaluating the predictive value of referrals over and above the information contained in our partner lender's screening procedure for graduation loans.

Specifically we estimate the following model separately for each survey wave S,

$$y_{it} = \alpha + \beta_S ReferredInRoundS_i + \gamma X_i + \phi_t + \epsilon_{it} \tag{10}$$

where y_{it} is a measure of borrower i's repayment behavior in month t, and $ReferredInRoundS_i$ is an indicator for whether borrower i was referred in survey round S (*Baseline*, *Fixed-Price*, and *Revenue-Share*).[15][16] We use double post lasso to select control variables X_i from the set of borrower characteristics presented in Panel A of Table A1. Due to our sample size, we include month when loan is due ϕ_t fixed effects, but not loan officer fixed effects. Because our sample comprises the universe of borrowers in the graduation loan portfolio over the relevant time horizon, standard errors are clustered at the borrower level (Abadie et al., 2017).

Within each regression model the sample comprises repayment data on borrowers who were referred in round S and subsequently graduated, and borrowers who were never referred in any round but who graduated after survey round S, so that they were eligible to be referred in survey round S. So for the baseline referral survey, the sample includes any borrower who was either referred at baseline or never referred, and who received a graduation loan sometime after December 1, 2018. For referrals collected in the $Fixed\text{-}Price$ survey it includes any borrower who was either referred in the $Fixed\text{-}Price$ round or never referred, and who received a loan after March 9, 2019. And in the $Post\text{-}Revenue\text{-}Share$ survey it includes any borrower who was either referred in the $Post\text{-}Revenue\text{-}Share$ round or never referred, and who received a loan after April 6, 2019. By holding fixed the comparison group to be those who were never referred in any round, this approach allows for evaluation of the predictive power of referrals collected in different survey rounds S by directly comparing the coefficients β_S.

We present these results for two time frames. The sample in Table 2a contains repayment

[15] For this part of the analysis, we combine referrals given in the first survey round (Baseline - November 2018) and the second survey round ($Pre\text{-}Fixed\text{-}Price$- last week of February 2019) since the loan officer incentives were the same for both those rounds. As we showed in Section 4, the passage of time has no significant effect on the number of referrals that we received.

[16] Though loan officers were instructed not to refer borrowers whom they had referred in prior rounds, several loan officers referred borrowers more than once. In these cases, we treat the borrower as referred only in the first round that the loan officer named them.

data from December 1, 2018 to March 1, 2020 just before Chile's shutdown for COVID-19. At this point our partner lender implemented a 3 month repayment freeze. The sample in Table 2b contains data from the relevant survey waves to December 30, 2023, at which point all graduation loans in our study had either been fully repaid or written off. In both tables, the four outcome variables we examine are whether a borrower is at least 15 days late (columns 1 and 2), whether she is at least 90 days late (columns 3 and 4), whether she has "defaulted" on her graduation loans (columns 5 and 6), and the total value in default (columns 7 and 8).[17] For graduation loans, default is classified as being late in repayment for 180 consecutive days, at which point borrowers are reported to the credit bureau and their debt is sold to a third party. Columns 1 - 4 represent regressions at the borrower-week level, and columns 5 - 8 represent regressions at the borrower level. Even columns include double-post lasso controls in Panel A of Table A1 and odd columns do not.

Beginning with the short-term repayment results in Table 2a, we see that with few exceptions, borrowers who were referred after the compensation changes exhibit better repayment behavior than those who were not referred. Estimates are highly stable with respect to the inclusion of controls. In fact, in many columns the double post lasso procedure does not select any controls at all – this is likely a result of the fact that the graduation loan officers use many of these observable characteristics in selecting which borrowers to graduate. That microcredit loan officer referrals are predictive of default even after accounting for a large battery of observable characteristics suggests that loan officers have valuable information about borrower repayment capacity that is not well encoded by observables.[18]

The magnitudes of the point estimates for referrals furnished after the compensation change are economically meaningful. For instance, compared to graduated borrowers who were never referred, graduated borrowers referred after the fixed-price or revenue-sharing contracts are 2.2 [SE: 0.7] percentage points less likely to default in a binary sense, and default on USD 49.0 [SE: 17.9] less, on average. The estimates for referrals furnished at baseline are about half as large, are never statistically significant, and in several cases the estimates are statistically significantly smaller than the corresponding estimates for

[17]We selected 15 days late as an outcome variable because this is the threshold after which late payment is reported to the credit bureau. 90 day lateness is a salient metric for our partner lender, as it is the reporting threshold for default in joint-liability lending.

[18]This echoes results from Hussam et al. (2021), which finds that community members have valuable information about their entrepreneur-peers that is not well encoded by observable characteristics. Of course, we cannot rule out the possibility that there are "soft characteristics" such as socioeconomic status that are observable to the lender but not to us as econometricians, which are highly correlated with loan officer referrals.

the fixed-price and revenue-sharing contracts. The fact that borrowers referred after the fixed-price and revenue-sharing contracts have better repayment profiles than those referred at baseline suggests that loan officers were withholding referrals of their best borrowers prior to the compensation shifts.

The estimates in Table 2b, which expands the repayment window from the relevant referral survey to the loans' closure, tell a very similar story. Baseline referrals are not predictive of default, while the pooled referrals furnished after the two compensation changes are predictive (the estimates for the revenue-sharing contract are now noisier and not statistically significant). The principle difference is that the point estimates are now far larger, as our partner lender suffered more default in the overall portfolio during the pandemic, while borrowers referred after the compensation changes maintained relatively good repayment records. For instance, borrowers referred after the fixed-price or revenue-sharing contracts are 20.5 [SE: 8.0] percentage points less likely to default in a binary sense, and default on USD 295.9 [SE: 141.7] less, on average.[19]

The above results suggest that prior to the introduction of the novel contracts, microcredit loan officers were withholding referrals of the borrowers that our partner lender would most like to graduate. We will show in Section 6 that, relative to the borrowers referred at baseline, the borrowers referred after the contractual changes were also more profitable in the microcredit portfolio, offering an explanation for why these referrals were initially withheld. This is an important conflict of interests–inherent in the baseline incentive scheme–between loan officers and our partner lender, and more broadly between loan officers and the goal of graduating qualified borrowers out of microcredit. One potential caveat to this conclusion is the possibility that in graduating referred borrowers there are negative spillovers on the borrowers who are left behind in the joint-liability groups. We consider this possibility in Appendix Section B and do not find any evidence of such negative spillovers.

Referrals Predict Borrower Business Growth Following Graduation Loans

Next, we establish that loan officer referrals are predictive of how much borrowers' profits grow following receipt of a graduation loan. As in the case of predicting repayment, we

[19]Finally, in Table A3 we re-estimate Specification 10, but replace $ReferredInRoundS_i$ three dependent variables that capture the strength of each referral. Recall that our loan officer survey elicited a 1-5 measure of referral strength. Hence we investigate potential non-linearities in referral strength by regressing outcomes on a dummy for referred with strength 1-3, a dummy for referred with strength 4, and a dummy for referred with strength 5. Results are similar and indicate little variation in referral quality by strength.

show that referrals furnished after the contract changes are strongly predictive of business growth, while those furnished at baseline are not.

We note at the outset that profit growth following receipt of a graduation loan is not necessarily indicative of the impact of the graduation loan on a borrowers' profits. It may be that graduation loan officers choose to give graduation loans to borrowers whose businesses are about to experience outsized growth regardless of the whether or not they receive a loan. Nevertheless, information about how much a borrower's business grows after receiving a graduation loan is of significant interest to a lender, all the more so if they have a social mission. Either this information indicates how much a borrower will benefit from receiving a graduation loan, or it indicates how much their business is about to grow regardless of the loan, and therefore how likely they are to be able to repay the loan.

To establish the predictive power of loan officer referrals on profit growth following a graduation loan we utilize the time series of business profits, before and after borrowers graduate to larger loans. Our administrative data allow us to observe a snapshot of each borrower's monthly profit at their fourth loan cycle, prior to any borrower in our sample graduating, and again when they renew their loans from 2020 to 2022.

We estimate the following model separately for each survey wave S,

$$y_{it} = \alpha + \beta_S ReferredInRoundS_i + \gamma Graduation_{it} + \delta_S ReferredinRoundS_i * Graduation_{it} + \phi X_i + \varepsilon_{it} \tag{11}$$

where y_{it} is borrower i's profit in period t, $ReferredInRoundS_i$ is an indicator for whether borrower i was referred in survey round S, and $Graduation_{it}$ is an indicator variable taking a value of 1 if borrower i received a graduation loan at or before period t and 0 otherwise. We use double post lasso to select control variables X_i from the set of borrower characteristics presented in Table A1. Additionally, all regressions control for the time elapsed between our baseline recording of profits – borrower i's fourth loan cycle – and period t. Borrower fixed effects are included in alternative specifications. Standard errors are clustered at the borrower level. Due to sample size limitations, we pool referrals for borrowers referred after the fixed-price and revenue-sharing contracts.

Within each regression model the sample comprises profits data on borrowers who were referred in round S and subsequently graduated, and borrowers who were never referred in any round but who graduated after survey round S, so that they were eligible to be referred in survey round S. We restrict the sample to borrowers who eventually receive graduation loans.

The estimates are presented in Table 3. Three features of the results are of note. First, the estimate of γ indicates that on average, borrowers who were not referred in any round experienced significant growth in their profits after receiving a graduation loan, though this diminishes with the inclusion of controls and borrower fixed effects. Estimates in Panel A indicate that their monthly profits grew by USD 336 [SE: 256] to 924 [SE: 264]. Second, from the estimates of $\delta_{Baseline}$, we cannot reject that the borrowers referred in the baseline survey wave did not experience any additional profits growth upon receiving a graduation loan relative to borrowers who were never referred. Finally, the estimates of $\delta_{FP \vee RS}$ indicate that borrowers referred after the compensation change experienced nearly twice as much profit growth upon receiving a graduation loan, relative to borrowers referred at baseline and those never referred. For instance, the estimate in Panel B, column 1 indicate that borrowers referred after the compensation changes experienced an additional USD 1044 [SE: 556] in profit growth. Across all of the columns, $\delta_{FP \vee RS}$ is larger than $\delta_{Baseline}$ (p-value .09).

That referrals furnished after the compensation changes predict more business growth following the graduation loan than those furnished at baseline further underscores the misalignment of interests between loan officers and our partner lender. And to the extent that some portion of the business growth following graduation loans is due to receiving the graduation loan, these results also highlight the misalignment of interest between loan officers and their borrowers.

6 Evaluating Theoretical Predictions

Having established that both fixed-price and revenue-sharing contracts improved the quantity and quality of referrals, we now turn to testing the predictions of the model outlined in Section 2. Specifically, we evaluate three predictions.

1. Proposition 2 indicates that the fixed-price contract should induce higher quality referrals for intrinsically motivated loan officers.

2. Proposition 3 indicates that the revenue-sharing contract should improve the quality of referrals for loan officers with low intrinsic motivation.

3. Proposition 3 also indicates that the revenue-sharing contract should improve the quality of referrals for loan officers with high intrinsic motivation, but less so than for those with low intrinsic motivation.

To evaluate these predictions, we examine the extent to which loan officer referrals predict repayment in the microcredit portfolio. We rely on repayment in the microcredit portfolio, rather than the graduation loan portfolio as the microcredit portfolio has far more data – all borrowers in our data have at least one loan cycle in the microcredit portfolio after the referral surveys – and therefore we have more statistical power to identify heterogeneous referral quality in the microcredit repayment data.[20]

We first begin by identifying which microcredit loan officers are intrinsically motivated. Proposition 4 indicates that loan officers with a higher degree of intrinsic motivation should provide higher quality referrals in the baseline survey, at which point no explicit compensation was offered for referrals. Correspondingly, for each loan officer, we estimate the correlation between whether they referred a borrower at baseline and the likelihood that the borrower subsequently defaulted in the microcredit portfolio.We define a loan officer i as *intrinsically motivated*, $IM_i = 1$ if they are below median in this regard (i.e. they baseline referrals are better than average at predicting good repayment).[21] Figure 3 is a histogram plotting the distribution of the correlation between each loan officer's baseline referrals and borrower default. The vertical dotted line denotes the median.[22] We note that while our regression specifications divide loan officers based on whether they provided below or above median quality referrals at baseline, Figure 4 presents a graphical variant of the analyses to follow by plotting the full distribution of loan officer referral qualities at baseline.

Proposition 2 indicates that after the implementation of the fixed-price contract, the referrals of intrinsically motivated loan officers should be more predictive of repayment than

[20]One important note about these data is that within each joint-liability group, borrowers are divided into subgroups of about 4 borrowers that jointly submit their repayments. Thus, with few exceptions, repayment status is constant within each subgroup. We account for this feature by clustering the standard errors of the regressions to follow at the joint-liability group level.

[21]Of course, other factors such as luck might also influence the quality of referrals elicited at baseline. These factors would serve to add noise to our classification of intrinsically motivated loan officers and would thus would bias us away from finding significant results in our subsequent analyses.

[22]For robustness, we repeat our analysis of Table 4 redefining an intrinsically motivated loan officer as one who scored below the median when we estimate the correlation between whether they referred a borrower at baseline and the likelihood that the borrower subsequently was at least 15 and 90 days late in the microcredit portfolio, and the likelihood that the amount that the borrower subsequently defaulted on in the microcredit portfolio. These results are presented in Tables A5, A6, and A7. In each case the results of these analyses are similar.

those of non-intrinsically motivated loan officers. We evaluate this prediction with the following regression.

$$y_{ijt} = \alpha + \beta_{FP} IM_j + \gamma_{FP} Referred_{ij} + \delta_{FP} Referred_{ij} * IM_j + \gamma X_i + \psi_j + \phi_t + \epsilon_{ijt} \quad (12)$$

Here, the sample comprises all microcredit loans that were active from the start of the intervention period in February 22, 2019 to March 1, 2020 (the approximate start of Chile's Covid-19 lockdown). y_{ijt} represents the various measures of lateness and default for borrower i, managed by loan officer j at time t, $Referred_{ij}$ is a dummy taking a value of 1 if borrower i was referred by loan officer j in the Fixed-Price survey round and 0 otherwise, and IM_j is a dummy taking a value of 1 if loan officer j is intrinsically motivated, as defined above, and 0 otherwise. ψ_j is a loan officer fixed effect, and ϕ_t is a month-year fixed effect. Standard errors are clustered at the joint-liability group level. Where utilized, controls are selected using double-post lasso. The prediction of Proposition 2 is that $\delta_{FP} < 0$, i.e. that the referrals are more predictive of (a lack of) default for intrinsically motivated loan officers.

The results are presented in Panel A of Table 4. Consistent with Proposition 2, the sign on δ_{FP} is negative across all outcome variables, and statistically significant for all outcome variables except for default amount (when loan officer fixed effects and controls are included). For instance, the estimate of δ_{FP} in column 5 implies that relative to the referral of a non-intrinsically motivated loan officer, the referral of an intrinsically motivated loan officer predicts a further reduction in the likelihood of default of 5.6 [SE: 1.5] percentage points. Further consistent with the theory, across all outcomes γ_{FP} is small and never statistically significant, indicating that loan officers who are not intrinsically motivated do not provide informative referrals following the fixed-price contract.

Next, Proposition 3 indicates that after the implementation of the revenue-sharing contract, the referrals of non-intrinsically motivated loan officers should be more informative than the referrals of the same loan officers following the fixed-price contract. We evaluate this prediction with the following regression specification.

$$y_{ijt} = \alpha + \beta_{RS} IM_j + \gamma_{RS} Referred_{ij} + \delta_{RS} Referred_{ij} * IM_j + \gamma X_i + \psi_j + \phi_t + \epsilon_{ijt} \quad (13)$$

The sample and variables are the same as in the previous specification with the exception that $Referred_{ij}$ is now a dummy taking a value of 1 if borrower i was referred by loan officer j in the Revenue-Share survey round and 0 otherwise. The prediction of Proposition 3 is that $\gamma_{RS} < \gamma_{FP}$, i.e. that for non-intrinsically motivated loan officers, referrals following the revenue-sharing contract should be more predictive of (a lack of) default than referrals following the fixed-price contract. Moreover, the proposition also predicts that $\delta_{RS} > \delta_{FP}$, i.e. that for intrinsically motivated loan officers, the quality of referrals should improve less in the revenue-sharing contract than for non-intrinsically motivated loan officers, as the former group furnished more high quality referrals in the fixed-price contract.[23]

The results are presented in Panel B of Table 4. Consistent with Proposition 3, γ_{RS} is negative and statistically significant throughout. Across all columns, $\gamma_{RS} < \gamma_{FP}$ and this comparison is statistically significant for all outcome variables except for default amount. Further consistent with the theory, $\delta_{RS} > \delta_{FP}$ across all columns, and this comparison is statistically significant for five of the columns. In other words, the revenue-sharing contract caused a larger increase in referral quality for non-intrinsically motivated loan officers than for intrinsically motivated ones.

Figure 4 presents graphical support for our model's predictions. Each observation in the graph corresponds to a single loan officer's referrals. The x-axis corresponds to the loan officer's intrinsic motivation θ, as proxied by the (negative of the) correlation between their baseline referrals and borrowers' subsequent default, so that more intrinsically motivated loan officers are plotted farther to the right. The y-axis plots the (negative of the) correlation between the loan officer's referrals in the fixed-price or revenue-sharing survey round and a borrower's subsequent default, so that the more accurate a loan officer's referrals the higher the observation appears on the y-axis. Fixed-price referrals are plotted in red, and revenue-sharing referrals are plotted in blue. Each dot in the figure corresponds to a bin-scatter partitioning the loan officers into 15 bins, plotting the average x- and y-values for loan officers in the bin.

Proposition 2 predicts that the more intrinsically motivated a loan officer is, the more

[23]To understand further where this prediction comes from, note that the quality of referrals for non-intrinsically motivated loan officers is $-\gamma_{FP}$ in the fixed-price contract, and $-\gamma_{RS}$ in the revenue-sharing contract. The corresponding expressions for intrinsically motivated loan officers are $-\gamma_{FP} - \delta_{FP}$ and $-\gamma_{RS} - \delta_{RS}$. The negative signs correspond to the fact that borrower quality is the negative of our key outcome variables, which measure default. The improvement of non-intrinsically motivated loan officers across the successive contracts is $\gamma_{FP} - \gamma_{RS}$. And the improvement for intrinsically motivated loan officers is $(\gamma_{FP} + \delta_{FP}) - (\gamma_{RS} + \delta_{RS})$. That non-intrinsically motivated loan officers improve more than intrinsically motivated loan officers then corresponds to $\delta_{RS} > \delta_{FP}$.

accurate their referrals will be in the fixed-price survey round – i.e. that the line of best fit for the fixed-price survey round will have a positive slope. This is corroborated by Figure 4.

Next, Proposition 3 indicates that the revenue-sharing contract should improve the accuracy of referrals for all loan officers, but more for loan officers with low intrinsic motivation – i.e. relative to the line of best fit for the fixed-price survey round, the corresponding line for the revenue-sharing survey round will be shifted upwards and exhibit a clockwise rotation. These predictions are borne out in Figure 4 as well.

Finally, we note that While the results are consistent with the predictions of our theory, they are importantly *not* consistent with the alternative theory whereby some loan officers make informative referrals each time they are surveyed and others do not. This alternative theory predicts that loan officers who make informative referrals at baseline (those we define to be intrinsically motivated) would also make informative referrals after the fixed-price contract announced, consistent with Proposition 2. However, this alternative theory is inconsistent with Proposition 3 and our results, which find that the loan officers who made uninformative referrals at baseline made informative referrals after the revenue-sharing contract was announced.

7 Generalizability of Results

How far do the results of this study extend to organizations beyond our partner lender? We first consider the case of other microfinance institutions. Our proposed mechanism relies on four features.

1. The microfinance institution has an internal graduation program.
2. Distinct loan officers manage the microcredit portfolio and the graduation portfolio.
3. Microcredit loan officers are compensated based on the size and/or repayment rate of their portfolio.
4. Microcredit loan offices do not receive any special bonus when their borrowers graduate out of microcredit.

To address the extent of these managerial practices amongst microfinance institutions we draw on two data sources.

Our first indication comes from the Mix Market dataset. These data were collected annually from 2002 to 2017, capturing the management practices of over 3100 microfinance institutions around the world. Of these institutions, slightly more than half report having internal graduation programs, defined as having both a "micro loan" and at least one of an "SME loan" or "Large loan."[24] Of those with graduation programs, more than 80% report compensating their loan officers based on at least one of the size or repayment rate of their portfolio. These are two critical factors that give rise to a misalignment of incentives between loan officers and their borrowers. However the MIX Market dataset does not contain information on whether micro and graduation loans are managed by different loan officers, and it does not contain information on whether loan officers are given a special bonus for helping a borrower to graduate.

To remedy these shortcomings we conducted a novel survey of 46 microfinance institutions in Latin America, India the Middle East, and North Africa. These institutions were reached through personal contacts of our partner lender, and the Harvard Business School research centers in India, Latin America, and the Middle East and North Africa, and are listed in Online Appendix Figure A3. Our survey was distributed to managers within these institutions who reported to know about how loan officers were organized and compensated.

Of these 46 institutions, 67% report having an internal graduation program.[25] And of those MFIs with an internal graduation program, 48% have distinct loan officers manage each loan product, compensate loan officers based on the size or risk of their portfolio, and do not provide special bonuses for loan officers whose borrowers graduate to larger loans. That is, compensation practices of these MFIs induce a similar misalignment of interests between loan officers and borrowers as was present with our partner lender at the time of our study.[26]

Table A8 compares our sample of responding microfinance institutions to the full popula-

[24]The Mix Market data allow for some exploration into what characteristics of a microfinance institution are correlated with having a graduation loan. Online Appendix Table A9 indicates that microfinance institutions with graduation programs are about 3 times as large on average, in terms of assets under management, and are more likely to be located in Africa and less likely to be in Latin America. In terms of social metrics – likelihood of targeting "very poor" and "low-income" households, and providing various auxiliary non-financial services – microfinance institutions with and without graduation programs are very similar.

[25]Specifically, 67% of responding managers reported that their MFI "offers a loan product that is larger than your standard microloan."

[26]Interestingly, of those MFIs whose practices do not induce a misalignment of interests between loan officers and borrowers, 62% have a single loan officer manage both loan products, 38% utilize different loan officers but do not provide monetary incentives for the size and repayment rate of loan officers' portfolios, and 6% offer a bonus to loan officers when a borrower graduates out of their portfolio.

tion of microfinance institutions in the MIX Market database, both in terms of number of borrowers and assets under management. When available, data on portfolio size comes from Mix Market, and when not available we attempted to gather this information from each organization's website. Column 2 presents the difference between the two samples, controlling for the year of data collection. Compared to the full population of microfinance institutions, those that responded to our survey are about 2.4 times as large in terms of assets under management, and 2.0 times as large in terms of borrowers (Panel A). However these differences diminish somewhat when restricting the population of microfinance institutions to those from the countries represented in our survey sample and are no longer statistically significant (Panel B).

Figure 5 plots the average portfolio size in terms of assets under management (top) and borrowers (bottom) for the microfinance institutions with graduation programs in our survey sample that do and do not share our partner lender's incentive problem. There is no statistically significant difference in these metrics between the two groups, indicating that the compensation problems we identify are not relegated to small microfinance institutions. If anything, the point estimates suggest that the microfinance institutions that suffer from this problem are somewhat larger, with the group that shares the incentive problem having an average of USD 352 million in assets under management and 315 thousand borrowers, compared to averages of USD 220 million and 192 thousand borrowers for the microfinance institutions that do not share the incentive problem.

The widespread prevalence of compensation practices that penalize loan officers when their borrowers graduate to larger loans (even internally) suggests that the results from this study may generalize to half of all microfinance institutions with graduation programs. Moreover, microfinance institutions with graduation programs tend to be quite large. In the MIX dataset, we find that microfinance institutions with graduation programs more than 3 times larger in terms of assets under management than those without. For those with graduation programs, graduation loans represent nearly 44% of their assets under management and 22% of their borrowers. Thus, these results suggest that a misalignment of interests between loan officers and their borrowers may be an important hindrance to the impact that microcredit could have on livelihoods.

More broadly, the model of Section 2 offers guidance as to how our results may generalize to other organizations. Our results may inform contract design in any firm that relies on employees to refer opportunities to one another, and where there is an incentive for the referring employee to inefficiently retain the opportunity for their own benefit (such as the types of firms highlighted in our introduction). In settings where employees are intrinsically motivated, our results indicate that fixed-price contracts – which pay a referral fee that is independent of the performance of the referred opportunity – are likely to be optimal. When employees lack intrinsic motivation, our results indicate that revenue-sharing contracts – which compensate employees based on the subsequent performance of their referred opportunities – may be necessary.

The fixed-price contract we study, which offers loan officers a grace period during which time the referred borrower is treated as if it were still in the referring loan officer's portfolio, could be directly translated to some other organizational settings. For instance, when a manager chooses to refer a talented employee for promotion to another team, the referring manger could be offered a grace period during which time their performance targets are adjusted to reflect the loss of an employee. In settings where there may not be a direct analogue of our fixed-price contract (e.g. professional service firms and sales, as discussed in our introduction), our results still indicate that intrinsically motivated employees may respond well to fixed-price contracts more generally.

The revenue-sharing contract we study, which compensates loan officers as a function of the performance of the referred borrower in the graduation portfolio, could be translated to any setting in which it is easy to directly track the revenue generated by a particular referred opportunity (e.g. in sales, where revenue is directly attributable to particular customers). In other settings, compensation schemes that align the pay of an employee with the performance of the whole firm would retain some of the benefits of a revenue-sharing contract. Of course, if any particular referral is only a small contributor to a firm's total performance, these equity-like contracts may induce only weak incentives for efficient referrals.

8 Discussion

Countless firms rely on internal referrals between employees to ensure that tasks and resources are efficiently allocated. Yet in many such settings, employees may have an incentive to inefficiently retain these opportunities for their own benefit. How should firms compensate employees to induce optimal referrals?

Our theoretical results indicate that when employees are intrinsically motivated, a fixed-price contract – where compensation is independent of the performance of the referred opportunity – is optimal. When agents lack intrinsic motivation, revenue-sharing contracts – which condition the compensation of the referring employee on the performance of the referred opportunity – may be necessary. In collaboration with one of Chile's largest microfinance institutions, we implemented both a fixed-price and revenue-sharing contract to induce microcredit loan officers to refer to borrowers to a larger graduation loan. We demonstrate that each of these contracts improved the quantity and quality of referrals. Consistent with the theory, the fixed-price contract performed better for intrinsically motivated loan officers and the revenue-sharing contract performed better for non-intrinsically motivated loan officers.

Beyond providing evidence about optimal referral contracts, our study has important implications for microfinance policy. Microfinance institutions around the world have adopted graduation programs, whereby borrowers can graduate from group microloans to significantly larger individual loans while remaining customers of the same lender. Several studies have demonstrated the potential of these larger loans to significantly benefit microentrepreneurs (Bari et al., 2021; Bryan et al., 2022). In this paper, we demonstrate that common features of loan officers' compensation contracts –such as rewards for portfolio size and good repayment records – implicitly penalize them when their borrowers graduate and cause loan officers to impede their borrowers' graduation.

Utilizing the MIX Market dataset as well as a novel survey of 46 microfinance institutions around the world, we document the widespread usage of incentive schemes that penalize loan officers for borrower graduation. Thus, our results may illuminate a new path to increase the impact microcredit has on entrepreneurship and business growth. Microfinance institutions and their loan officers often face an inherent tension between their own profitability and supporting their borrowers' ultimate graduation out of microcredit (Liu and Roth, 2022). Our results demonstrate that this tension strongly deters loan officers from supporting their borrowers.

Policies that reward loan officers and microfinance institutions when their borrowers graduate to self-sufficiency or more formal sources of credit may enhance rates of graduation and the impact of microcredit. After the completion of our study, our partner lender took this insight to heart. Rather than permanently implementing either of the compensation schemes we study in this paper, our partner undertook a more significant reorganization. Prior to our study, the microcredit loans and graduation loans were siloed, being managed by different loan officers but also entirely different organizational hierarchies. After our study, our partner lender merged the two loan programs into one managerial hierarchy, so that at each branch, one manager oversaw the full team of loan officers across both the joint-liability and graduation loan portfolios. That branch manager was therefore able to internalize the rewards of graduating qualified borrowers as well as the costs of graduating unqualified borrowers. While this appears to be an elegant solution for organizations that house both a standard microcredit product and a graduation loan, government and other third party intervention (e.g. by donors and investors) may be required to align the incentives of microfinance institutions with the graduation of their borrowers in situations when borrower graduation necessarily implies that they lose a valuable customer.

Finally, we note that our experimental design may be useful for other studies in large organizations. Managers are often reluctant to treat employees differently from one another, especially regarding the way they are compensated. So, randomizing the timing of surveys relative to firm-wide changes enables researchers to evaluate the causal impact of a variety of managerial practices that are too sensitive to themselves be randomized.[27]

[27] see Bassi and Rasul (2017) for a similar design to estimate the impact of a Papal visit to Brazil on people's beliefs about fertility.

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Omitted Proofs from Section 2

Proof of Proposition 1

Let
$$y_0^{LS} \equiv \text{argmax}_y \left\{ y - \psi\left(\frac{y}{\eta v_0}\right) + \theta W\left(v_0, \frac{y}{\eta v_0}, l\right) \right\}$$
and let
$$y_1^{LS} \equiv \text{argmax}_y \left\{ y - \psi\left(\frac{y}{\eta v_1}\right) + \theta W\left(v_1, \frac{y}{\eta v_1}, l\right) \right\}$$

There is a fixed-price contract p that induces efficient referrals only if inequalities 1 and 4 are satisfied:

$$y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right) + \theta W\left(v_0, \frac{y_0^{LS}}{\eta v_0}, l\right) \geq \bar{u}_l + p + \theta W\left(v_0, \frac{y_h\left(v_1|v_1\right)}{v_1}, h\right)$$

and
$$p + \bar{u}_l + \theta W\left(v_1, \frac{y_h\left(v_1|v_1\right)}{v_1}, h\right) \geq y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) + \theta W\left(v_1, \frac{y_1^{LS}}{\eta v_1}, l\right)$$

Inequality 1 is the incentive constraint that dictates that the low-skill loan officer should keep low-value opportunities, and inequality 4 is the incentive constraint that dictates the low-skill loan officer should refer the high-value opportunities. Together these imply

$$\theta \geq \frac{y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) - \left(y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right)\right)}{\Delta W_0 + \Delta W_1}$$

where $\Delta W_0 \equiv W\left(v_0, \frac{y_0^{LS}}{\eta v_0}, l\right) - W\left(v_0, \frac{y_h(v_0|v_1)}{v_1}, h\right)$ is the social welfare gain of having the low-skill loan officer (rather than the high-skill loan officer) handle the low-value opportunity, and $\Delta W_1 \equiv \left(W\left(v_1, \frac{y_h(v_1|v_1)}{v_1}, h\right) - W\left(v_1, \frac{y_1^{LS}}{\eta v_1}, l\right)\right)$ is the social welfare gain of having the high-skill loan officer (rather than the low-skill loan officer) handle the high-value opportunity. The numerator of the above inequality is the difference in net revenue (income minus effort cost) when the low-skill loan officer retains the high-value opportunity relative to when they retain the low-value opportunity. Clearly the right hand side of the above inequality is positive.

Therefore, when $\theta \geq \bar{\theta} \equiv \frac{y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) - \left(y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right)\right)}{\Delta W_0 + \Delta W_1}$, there exists a fixed-rate contract that induces efficient referrals.

In this case, inequality 2 implies that the high-skill loan officer exerts first-best effort conditional on receiving the high-value opportunity, and therefore the first-best outcome is achieved so long as their individual rationality constraint (inequality 3) is satisfied.

Let $p^* \equiv y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) + \theta W\left(v_1, \frac{y_1^{LS}}{\eta v_1}, l\right) - \bar{u}_l - \theta W\left(v_1, \frac{y_h(v_1|v_1)}{v_1}, h\right)$ be the lowest transfer that induces efficient referrals. If

$$y_h(v_1|v_1) - \psi\left(\frac{y_h\left(v_1|v_1\right)}{v_1}\right) - p^* \geq \bar{u}_h$$

then the fixed contract with rate transfer p^* induces the first best outcome. Otherwise there is no contract that induces the low-skill loan officer to refer high-value opportunities while also satisfying the high-skill loan officer's individual rationality constraint.

When $\theta < \bar{\theta}$, there is no fixed-price contract that induces the low-skill loan officer to refer high but not low-value opportunities. In this case, revenue sharing ($s > 0$) is necessary to induce informative referrals, and the high-skill loan officer's effort incentive compatibility constraint (inequality 2) implies they will exert less than first-best effort. This completes the proof of Proposition 1

We now make several comments about the result's robustness to various extensions. First, suppose that the high-skill loan officer is also intrinsically motivated, with parameter $\theta_h > 0$. This would manifest in the high-skill agent's incentive compatibility constraint 2, which would now be

$$y_h\left(v_1|v_1\right) = \underset{y}{\operatorname{argmax}}\left(1-s\right)y - p - \psi\left(\frac{y}{v_1}\right) + \theta_h W\left(v_1, \frac{y_h\left(v_1|v_1\right)}{v_1}, h\right) \tag{14}$$

It is immediate that the high-skill loan officer would then still exert first-best effort under the fixed-price contract and less than first-best effort under the revenue-sharing contract and thus the proof would proceed unchanged.

Next we consider the model extension where there is an idiosyncratic fixed cost $\varepsilon \sim F$ of servicing the client, for some probability distribution F with bounded support.

Let $\bar{\varepsilon}$ be the upper bound of the support of the distribution and $\underline{\varepsilon}$ be the lower bound. Then following the exact same logic as the proof above, it can be seen that a fixed-price contract can induce efficient referrals if and only if

$\theta \geq \bar{\theta}' \equiv \frac{y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) - \left(y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right)\right) - (\underline{\varepsilon} - \bar{\varepsilon})}{\Delta W_0 + \Delta W_1}$

Otherwise, as above, a revenue-sharing contract is necessary to induce efficient referrals and the high-skill loan officer exerts less than first-best effort. ■

Proof of Proposition 2

Consider any fixed-price contract p, and let $y_h\left(v_1|v_1\right)$ be the output prescribed by the high-skill loan officer when they receive the high value opportunity. Then $y_h\left(v_0|v_1\right) \equiv y_h\left(v_1|v_1\right)\frac{v_0}{v_1}$ is the output produced when the high-skill loan officer exerts the prescribed effort but receives the low-value opportunity. Once again, let

$$y_0^{LS} \equiv \text{argmax}_y \left\{ y - \psi\left(\frac{y}{\eta v_0}\right) + \theta W\left(v_0, \frac{y}{\eta v_0}, l\right)\right\}$$

and let

$$y_1^{LS} \equiv \text{argmax}_y \left\{ y - \psi\left(\frac{y}{\eta v_1}\right) + \theta W\left(v_1, \frac{y}{\eta v_1}, l\right)\right\}.$$

The low-skill loan officer refers the low-value case if and only if

$$y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right) + \theta W\left(v_0, \frac{y_0^{LS}}{\eta v_0}, l\right) - \varepsilon \leq p + \bar{u}_l + \theta W\left(v_0, \frac{y_h\left(v_0|v_1\right)}{v_1}, h\right)$$

which occurs with probability $1 - F\left(y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right) - p - \bar{u}_l + \theta \Delta W_0\right)$, where $\Delta W_0 \equiv W\left(v_0, \frac{y_0^{LS}}{\eta v_0}, l\right) - W\left(v_0, \frac{y_h(v_1|v_1)}{v_1}, h\right) > 0$. Clearly $F\left(y_0^{LS} - \psi\left(\frac{y_0^{LS}}{\eta v_0}\right) - p - \bar{u}_l + \theta \Delta W_0\right)$ is increasing in θ, so the probability of a low-quality referral is decreasing in θ.

Similarly, the low-skill loan officer refers the high-value case if and only if

$$p + \bar{u}_l + \theta W\left(v_1, \frac{y_h\left(v_1|v_1\right)}{v_1}, h\right) \geq \max_y y - \psi\left(\frac{y}{\eta v_1}\right) + \theta W\left(v_1, \frac{y}{\eta v_1}, l\right) - \varepsilon$$

which occurs with probability $1 - F\left(y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) - p - \bar{u}_l - \theta \Delta W_1\right)$ where $\Delta W_1 \equiv \left(W\left(v_1, \frac{y_h(v_1|v_1)}{v_1}, h\right) - W\left(v_1, \frac{y_1^{LS}}{\eta v_1}, l\right)\right) > 0$. Clearly $F\left(y_1^{LS} - \psi\left(\frac{y_1^{LS}}{\eta v_1}\right) - p - \bar{u}_l - \theta \Delta W_1\right)$ is decreasing in θ, so the probability of a high-quality referral is increasing in θ. ■

Proof of Proposition 3 Relative to the fixed-price contract p, in the revenue-sharing contract (p, s) the benefit to the low-skill loan officer of referring a low-value case has decreased, and the benefit of referring a high-value case has increased. Therefore, all loan officers will only recommend high-value cases independent of their intrinsic motivation θ. The improvement in referral quality from the fixed-price contract to the revenue-sharing contract is therefore only a function of the average quality of referrals under the fixed-price scheme. Proposition 2 established that this is increasing in θ which implies the result. ∎

Proof of Proposition 4 The proof closely follows the proof of Proposition 2 and therefore is omitted. ∎

Main Tables and Figures

Table 1: Impact of the Compensation Change on Total Cumulative Referrals

	Total Cumulative Referrals							
	Between Officers		Within Officers	All Officers		All Officers		All Officers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_1: Fixed-Price	1.111***	1.086***	1.618***	1.330***	1.319***	1.292***	1.516***	1.609***
	(0.278)	(0.279)	(0.526)	(0.268)	(0.268)	(0.273)	(0.501)	(0.295)
β_2: Revenue-Share						2.142***	2.313***	2.428***
						(0.337)	(0.556)	(0.376)
β_3: Pre Fixed-Price								0.122
								(0.236)
Mean: Referrals Pre Fixed-Price	0.19	0.19	0.19	0.19	0.19	0.19	0.19	
	[0.86]	[0.86]	[0.86]	[0.86]	[0.86]	[0.86]	[0.86]	
Mean: Referrals at Baseline	19.42	19.42	20.47	19.77	19.77	19.78	19.78	19.97
	[26.70]	[26.70]	[31.00]	[28.21]	[28.21]	[27.83]	[27.83]	[27.59]
Branch FE	X	X		X	X	X		
Loan Officer FE			X				X	X
Loan Officer Controls		X			X	X		
Number of Loan Officers	241	241	123	241	241	241	241	241
Observations	241	241	246	364	364	592	592	821
p-value for F Test:								
$\beta_1 = \beta_2$						0.00	0.00	0.00
$\beta_1 = \beta_3$								0.00

Notes: **Specification**: Columns (1)-(2) implement Specification 5, Column (3) implements Specification 6, Columns (4)-(5) implement Specification 7, Columns (6)-(7) implement Specification 8, and Column (8) implements Specification 9. Standard errors are in parentheses. Columns (1) - (5) only include the February (pre Fixed-Price) and March (post Fixed-Price) survey waves, with the former being the omitted group. In columns (1) and (2), there are 123 officers randomized to pre Fixed-Price and 118 officers randomized to *only* post Fixed-Price for between officer regression. These regressions include a branch fixed effect and robust standard errors. In column (3), there are a total of 246 observations from the 123 officers who submitted their referrals both before *and* after the Fixed-Price contract for within loan officer regression. This regression includes a loan officer fixed effect and standard errors clustered at the loan officer level. Columns (4) and (5) include 246 observations from 123 officers observed twice in the pre and post Fixed-Price rounds, and 118 officers who are only observed once post Fixed-Price as a part of pooled regression. These regressions include a branch fixed effect and standard errors clustered at the loan officer level. Columns (6)-(7) include the round in February, the round in March, and the round in April (post Revenue-Share), in which we collected referrals from 228 loan officers. Pre Fixed-Price is the omitted group. Column (6) includes branch fixed effects, Column (7) includes a loan officer fixed effect, and standard errors clustered at the loan officer level. Relative to columns (6) and (7), column (8) also includes 229 officers from the November survey wave, which is the omitted group in this regression. Columns (2), (5), and (6) include loan officer controls, which include the total number of referrals made in November, size of total loan portfolio in November 2018, and number of borrowers in the loan officer's portfolio in November 2018. **Outcome variable**: Columns (1)-(8) report results on the total cumulative number of referrals made by a loan officer by each survey round.

Table 2a: Do Referrals Predict Default on Graduation Loans?

	Late $\geq$ 15 days		Late $\geq$ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Referrals								
$\beta_{Baseline}$: Baseline	-0.006	-0.002	-0.012	-0.010	-0.012	-0.010	-24.254	-24.254
	(0.016)	(0.015)	(0.008)	(0.007)	(0.020)	(0.019)	(43.621)	(43.559)
Mean: Not Referred	0.077	0.077	0.031	0.031	0.062	0.062	128.547	128.547
	[0.266]	[0.266]	[0.174]	[0.174]	[0.242]	[0.242]	[544.687]	[544.687]
Number of Borrowers	709	709	709	709	709	709	709	709
Observations	26725	26725	26725	26725	709	709	709	709
Panel B: Fixed-Price Referrals								
β_{FP}: Fixed-Price	-0.041***	-0.039***	-0.014**	-0.013**	-0.023***	-0.023***	-50.022***	-50.022***
	(0.011)	(0.012)	(0.005)	(0.006)	(0.008)	(0.008)	(18.263)	(18.218)
Mean: Not Referred	0.050	0.050	0.014	0.014	0.023	0.023	50.022	50.022
	[0.217]	[0.217]	[0.119]	[0.119]	[0.149]	[0.149]	[362.538]	[362.538]
Number of Borrowers	408	408	408	408	408	408	408	408
Observations	13159	13159	13159	13159	408	408	408	408
Panel C: Revenue-Share Referrals								
β_{RS}: Revenue-Share	0.021	0.021	-0.013**	-0.013**	-0.016**	-0.016**	-37.101**	-37.101**
	(0.044)	(0.044)	(0.006)	(0.006)	(0.007)	(0.007)	(17.923)	(17.869)
Mean: Not Referred	0.048	0.048	0.013	0.013	0.016	0.016	37.101	37.101
	[0.215]	[0.215]	[0.113]	[0.113]	[0.125]	[0.125]	[319.148]	[319.148]
Number of Borrowers	329	329	329	329	329	329	329	329
Observations	9456	9456	9456	9456	329	329	329	329
Panel D: Fixed-Price or Revenue-Share Referrals								
$\beta_{FP \vee RS}$: FP or RS	-0.018	-0.018	-0.015***	-0.015***	-0.022***	-0.022***	-49.029***	-49.029***
	(0.022)	(0.022)	(0.005)	(0.005)	(0.007)	(0.007)	(17.902)	(17.860)
Mean: Not Referred	0.051	0.051	0.015	0.015	0.022	0.022	49.029	49.029
	[0.221]	[0.221]	[0.121]	[0.121]	[0.148]	[0.148]	[358.981]	[358.981]
Number of Borrowers	427	427	427	427	427	427	427	427
Observations	13723	13723	13723	13723	427	427	427	427
LASSO Controls		X		X		X		X
p-value for F test:								
$\beta_{Baseline} = \beta_{FP}$	0.042	0.042	0.825	0.825	0.541	0.541	0.528	0.528
$\beta_{Baseline} = \beta_{RS}$	0.564	0.564	0.905	0.905	0.822	0.822	0.758	0.758
$\beta_{Baseline} = \beta_{FP \vee RS}$	0.639	0.639	0.687	0.687	0.557	0.557	0.543	0.543

Notes: **Specification**: This table implements Specification 10. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. The regressor in each panel is an indicator variable for whether the borrower is referred in that particular round. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower-level regressions. For all panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Fixed-Price or Revenue-Share are excluded from Panel A. Borrowers referred at Baseline or Revenue-Share are excluded from Panel B. Borrowers referred at Baseline or Fixed-Price are excluded from Panel C. Only borrowers referred at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never referred at any round. The sample in each panel is limited to graduation loans that are disbursed after the respective incentive change. So Panel A includes graduation loans made after December 2018, Panel B and D includes loans made after March 9, 2019, Panel C includes loans made after April 6, 2019. Data utilized comes from repayment reports between November 1, 2018 and March 1, 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a graduation loan in the months after each referral wave, up to March 1, 2020. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a Graduation loan in the months after each referral wave, up to March 1, 2020. Columns (5)-(6) report results on an indicator variable for whether the borrower defaulted on a graduation loan in the months after each referral wave, up to March 1, 2020. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each referral wave, up to March 1, 2020.

Table 2b: Do Referrals Predict Default on Graduation Loans in the Long Run?

	Late $\geq$ 15 days		Late $\geq$ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Referrals								
$\beta_{Baseline}$: Referred at Baseline	0.009	0.011	-0.003	-0.001	0.011	0.011	16.378	29.718
	(0.019)	(0.018)	(0.012)	(0.012)	(0.042)	(0.042)	(90.422)	(88.984)
Mean: Not Referred	0.181	0.181	0.096	0.096	0.394	0.394	639.464	639.464
	[0.385]	[0.385]	[0.295]	[0.295]	[0.489]	[0.489]	[1092.147]	[1092.147]
Number of Borrowers	720	720	720	720	720	720	720	720
Observations	49645	49645	49645	49645	720	720	720	720
Panel B: Fixed-Price Referrals								
β_{FP}: Referred at Fixed-Price	-0.136***	-0.145***	-0.084***	-0.089***	-0.367***	-0.367***	-540.723***	-540.723***
	(0.022)	(0.023)	(0.010)	(0.012)	(0.024)	(0.024)	(49.595)	(49.475)
Mean: Not Referred	0.173	0.173	0.090	0.090	0.367	0.367	540.723	540.723
	[0.378]	[0.378]	[0.286]	[0.286]	[0.482]	[0.482]	[991.968]	[991.968]
Number of Borrowers	414	414	414	414	414	414	414	414
Observations	27584	27584	27584	27584	414	414	414	414
Panel C: Revenue-Share Referrals								
β_{RS}: Referred at Revenue-Share	0.012	0.012	-0.026	-0.026	-0.036	-0.036	-54.630	-45.384
	(0.058)	(0.057)	(0.035)	(0.035)	(0.148)	(0.148)	(271.237)	(270.307)
Mean: Not Referred	0.191	0.191	0.100	0.100	0.400	0.400	594.304	594.304
	[0.393]	[0.393]	[0.300]	[0.300]	[0.491]	[0.491]	[1021.442]	[1021.442]
Number of Borrowers	336	336	336	336	336	336	336	336
Observations	21656	21656	21656	21656	336	336	336	336
Panel D: Fixed-Price or Revenue-Share Referrals								
$\beta_{FP \vee RS}$: Referred at FP or RS	-0.069**	-0.069**	-0.057***	-0.057***	-0.205**	-0.205**	-295.890**	-295.890**
	(0.034)	(0.034)	(0.019)	(0.019)	(0.080)	(0.080)	(142.033)	(141.704)
Mean: Not Referred	0.174	0.174	0.090	0.090	0.372	0.372	543.240	543.240
	[0.379]	[0.379]	[0.287]	[0.287]	[0.484]	[0.484]	[987.185]	[987.185]
Number of Borrowers	433	433	433	433	433	433	433	433
Observations	28573	28573	28573	28573	433	433	433	433
LASSO Controls		X		X		X		X
p-value for F test:								
$\beta_{Baseline} = \beta_{FP}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\beta_{Baseline} = \beta_{RS}$	0.951	0.951	0.515	0.515	0.754	0.754	0.787	0.787
$\beta_{Baseline} = \beta_{FP \vee RS}$	0.034	0.034	0.008	0.008	0.013	0.013	0.048	0.048

Notes: **Specification**: This table implements Specification 10. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. The regressor in each panel is an indicator variable for whether the borrower is referred in that particular round. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower level regressions. For all panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Fixed-Price or Revenue-Share are excluded from Panel A. Borrowers referred at Baseline or Revenue-Share are excluded from Panel B. Borrowers referred at Baseline or Fixed-Price are excluded from Panel C. Only borrowers referred at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never referred at any round. The sample in each panel is limited to graduation loans that are disbursed after the respective incentive change. So Panel A includes graduation loans made after December 2018, Panel B and D includes loans made after March 9, 2019, Panel C includes loans made after April 6, 2019. Data utilized comes from repayment reports between November 1, 2018 and December 30, 2023. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a graduation loan in the months after each referral wave, up to December 30, 2023. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a Graduation loan in the months after each referral wave, up to December 30, 2023. Columns (5)-(6) report results on an indicator variable for whether the borrower defaulted on a Graduation loan in the months after each referral wave, up to December 30, 2023. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each referral wave, up to December 30, 2023.

Table 3: Do Referrals Predict Profits Growth for Borrowers who Graduated?

	Profits		
	(1)	(2)	(3)
Panel A: Referred at Baseline			
$\beta_{Baseline}$: Referred at Baseline	370.82	324.48	
	(264.35)	(257.03)	
$\gamma_{Baseline}$: Graduation	923.91***	335.70	392.84
	(264.44)	(256.23)	(398.31)
$\delta_{Baseline}$: Referred at Baseline $\times$ Graduation	-51.72	-55.21	-54.87
	(413.07)	(404.18)	(577.89)
Mean: Not Referred	1316.23	1316.23	1316.23
	[1368.81]	[1368.81]	[1368.81]
Number of Borrowers	166	166	166
Observations	332	332	332
Panel B: Referred at Fixed-Price or Revenue-Share			
$\beta_{FP\vee RS}$: Referred at FP or RS	97.90	-61.93	
	(474.93)	(201.52)	
$\gamma_{FP\vee RS}$: Graduation	1127.57***	526.07**	551.61
	(282.81)	(266.45)	(424.20)
$\delta_{FP\vee RS}$: Referred at FP or RS $\times$ Graduation	1044.06*	1033.21*	1033.67
	(556.35)	(543.06)	(780.02)
Mean: Not Referred	1325.17	1325.17	1325.17
	[1393.28]	[1393.28]	[1393.28]
Number of Borrowers	111	111	111
Observations	222	222	222
LASSO Controls		X	
Borrower FE			X
p-value for F-test:			
$\delta_{Baseline} = \delta_{FP\vee RS}$	0.09	0.09	0.09

Notes: **Specification**: This table implements Specification 11. The regressors are whether a borrower is referred in after the implementation of the Baseline (Panel A) or Fixed-Price or Revenue-Share (Panel B) contracts; an indicator variable (graduated) taking a value of 1 if the borrower received a graduation loan at or before period t and 0 otherwise; and an interaction of these two variables. For both panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Fixed-Price or Revenue-Share are excluded from Panel A, and borrowers referred at Baseline are excluded from Panel B. The omitted group in all panels is borrowers who were never referred at any round. The sample is limited to the borrowers that (1) graduated after the respective survey wave and (2) Have filled out an application form for a new loan after 2020. Standard errors are clustered at the borrower level. All columns include a control for the number of years that pass between the pre-graduation and post-graduation profits data collection. Column 1 does not include any additional control variables. Column 2 includes double-post lasso controls from Panel A of Table A1. Column 3 includes borrower fixed effects. **Outcome variable:** The outcome variable is business profits. There are two observations per borrower - one before graduation and one after. Profits are bottom-coded at the 1th percentile and top-coded at the 99th percentile

Table 4: Interaction between contract structure and intrinsic motivation

	15 Days		90 Days		Defaulted		Amount	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fixed-Price Referrals								
β_{FP}: IM LO	0.012***		0.002***		0.030***		7.443**	
	(0.003)		(0.000)		(0.007)		(3.674)	
γ_{FP}: Referred	0.001	0.003	-0.000	0.000	-0.007	-0.001	-4.673	-5.781
	(0.005)	(0.004)	(0.001)	(0.001)	(0.013)	(0.013)	(6.190)	(5.282)
δ_{FP}: IM LO $\times$ Referred	-0.022***	-0.018***	-0.003***	-0.003**	-0.052***	-0.045**	-15.815**	-11.342*
	(0.006)	(0.007)	(0.001)	(0.001)	(0.014)	(0.019)	(6.815)	(6.820)
Mean: Not Referred	0.012	0.012	0.002	0.002	0.029	0.029	13.045	13.045
	[0.109]	[0.109]	[0.041]	[0.041]	[0.167]	[0.167]	[105.088]	[105.088]
Number of Borrowers	43420	43420	43420	43420	43420	43420	43420	43420
Observations	1921612	1921612	1921612	1921612	43420	43420	43420	43420
Panel B: Revenue-Sharing Referrals								
β_{RS}: IM LO	0.012***		0.002***		0.030***		7.443**	
	(0.003)		(0.000)		(0.007)		(3.674)	
γ_{RS}: Referred	-0.011***	-0.010**	-0.002***	-0.001**	-0.029***	-0.033**	-13.045***	-10.977*
	(0.003)	(0.005)	(0.000)	(0.001)	(0.004)	(0.015)	(2.318)	(5.743)
δ_{RS}: IM LO $\times$ Referred	-0.012***	-0.002	-0.002***	-0.001	-0.030***	0.003	-7.443**	1.968
	(0.004)	(0.007)	(0.001)	(0.001)	(0.007)	(0.019)	(3.674)	(6.477)
Mean: Not Referred	0.012	0.012	0.002	0.002	0.029	0.029	13.045	13.045
	[0.109]	[0.109]	[0.041]	[0.041]	[0.167]	[0.167]	[105.088]	[105.088]
Number of Borrowers	43325	43325	43325	43325	43325	43325	43325	43325
Observations	1917319	1917319	1917319	1917319	43325	43325	43325	43325
LASSO Controls		X		X		X		X
Loan Officer FE		X		X		X		X
p-value for F test:								
$\gamma_{FP} = \gamma_{RS}$	0.016	0.034	0.061	0.087	0.078	0.079	0.171	0.406
$\delta_{FP} = \delta_{RS}$	0.079	0.097	0.068	0.181	0.078	0.061	0.171	0.098

Notes: **Specification**: This table implements Specification 12. Standard errors are in parentheses, clustered at the joint-liability (JL) group level. Standard deviations are in brackets. The regressors are a dummy variable for whether the loan officer is intrinsically motivated, whether a borrower is referred in after the implementation of the Fixed-Price (Panel A) or Revenue-Share (Panel B) contracts, and the interaction between these two variables. A loan officer is intrinsically motivated if she scored below the median when we estimate the correlation between whether they referred a borrower at baseline and the likelihood that the borrower subsequently defaulted in the microcredit portfolio. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower level regressions. For both panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Revenue-Share and Baseline are excluded from Panel A. Borrowers referred at Fixed-Price and Baseline are excluded from Panel B. The omitted group in all panels is borrowers who were never referred at any round. The sample in both panels is limited to joint-liability loans that are active during the intervention period (Feb 22, 2019 to Apr 6, 2019) and those made after the intervention period until March 1, 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1 and loan officer fixed effects. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a loan. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a loan. Columns (5)-(6) report results on an indicator variable for defaulted on a loan. Columns (7)-(8) report results on total amount defaulted.

Figure 1: Intervention and Survey Timeline

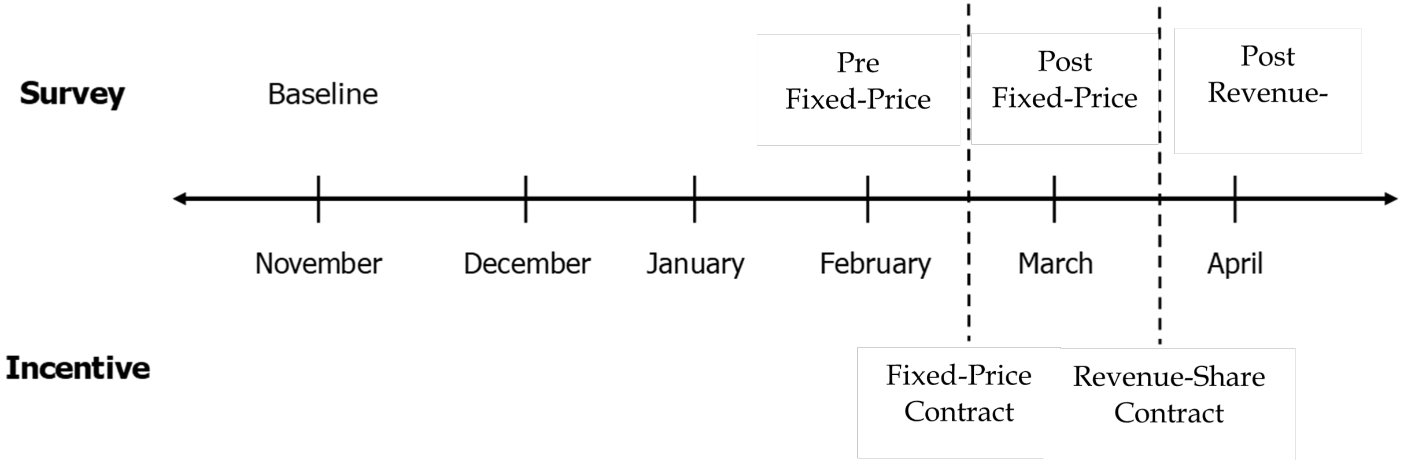
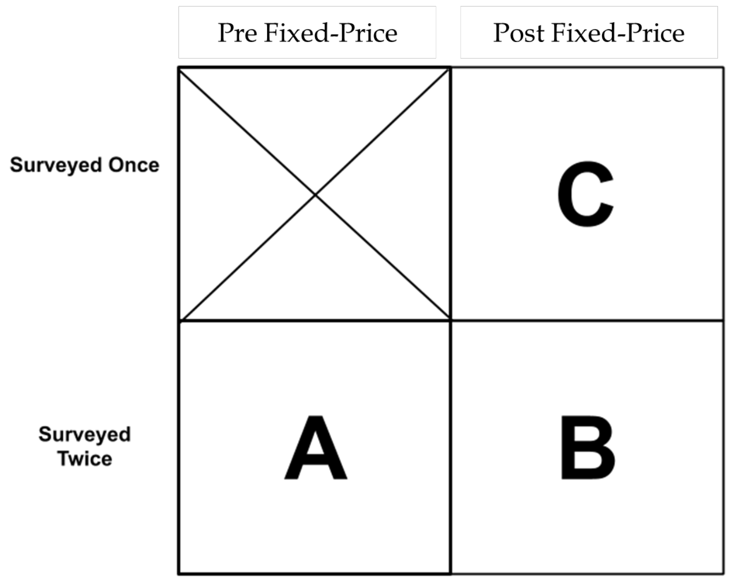
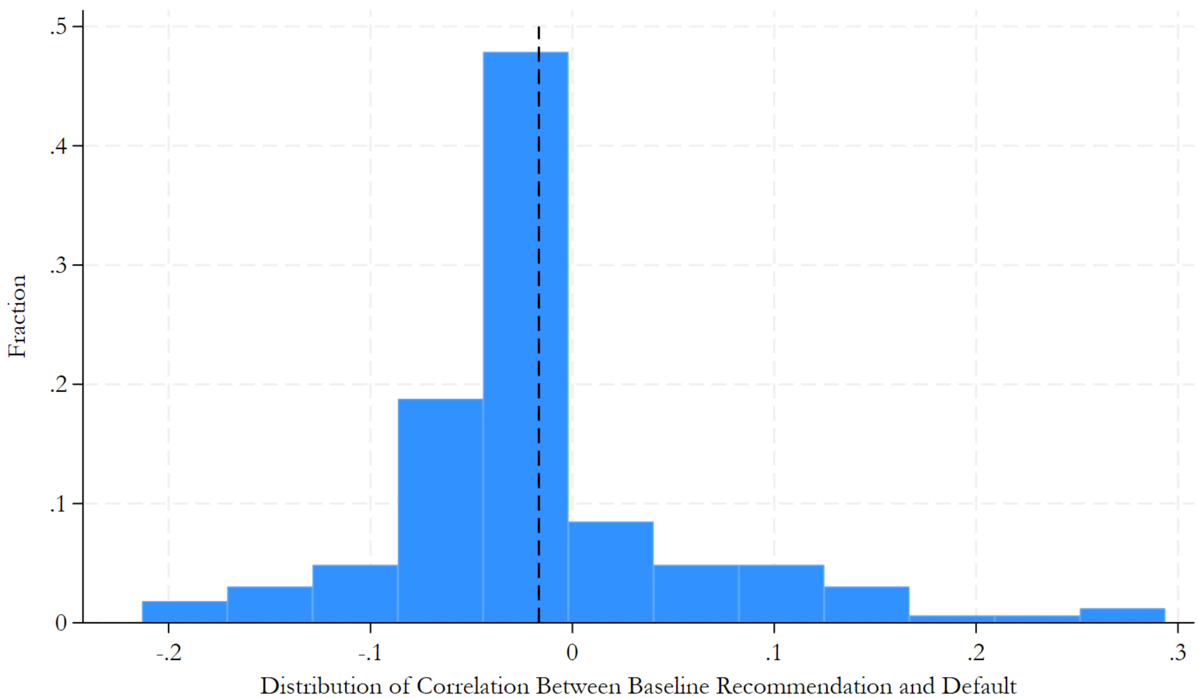


Figure 2: Randomization Design



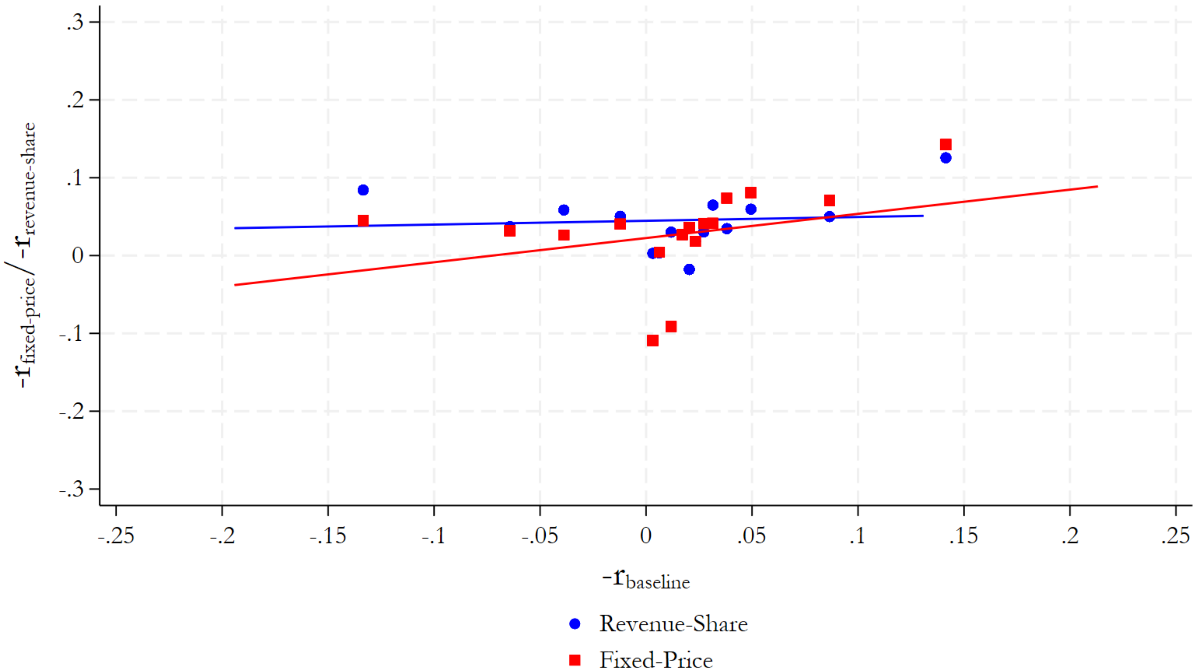
Notes: Loan officers were randomized into two groups before the Fixed-Price incentive change. In the Pre Fixed-Price survey wave, only one group - Group A - was asked to submit referrals. All loan officers were asked to submit referrals in the Post Fixed-Price survey wave - Group B is the group of loan officers who were also surveyed in the Pre Fixed-Price wave, and Group C is the group of loan officers who were only surveyed in the Post Fixed-Price wave. Our between-person identification strategy compares loan officers surveyed just before the Fixed-Price incentive change (Group A), to those only surveyed immediately after the Fixed-Price incentive change (Group C). Our within-person identification strategy compares the responses of those surveyed just before the Fixed-Price incentive change (Group A) to the responses of the same loan officers surveyed once again just after the incentive change (Group B).

Figure 3: Distribution of Correlation between Baseline Recommendation and Default



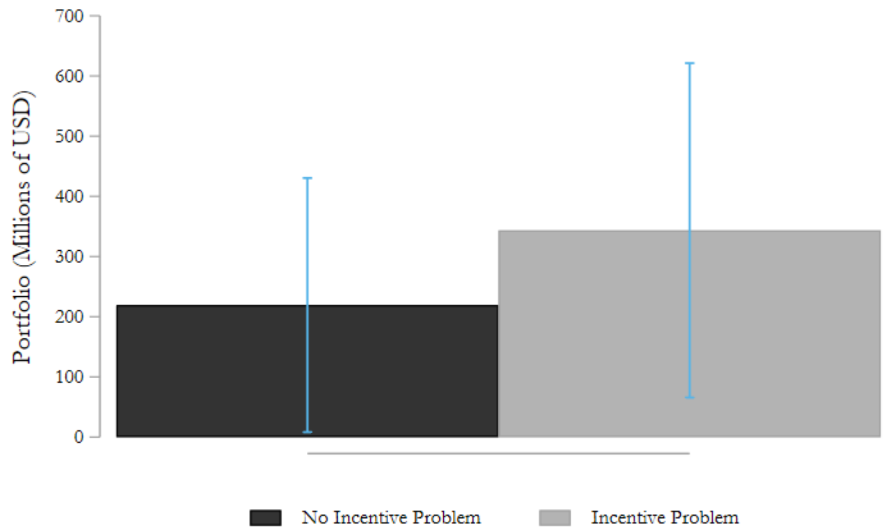
Notes: This figure presents a histogram of the correlation between baseline referrals and subsequent default in the microcredit portfolio. Each observation corresponds to the average correlation of a single loan officer.

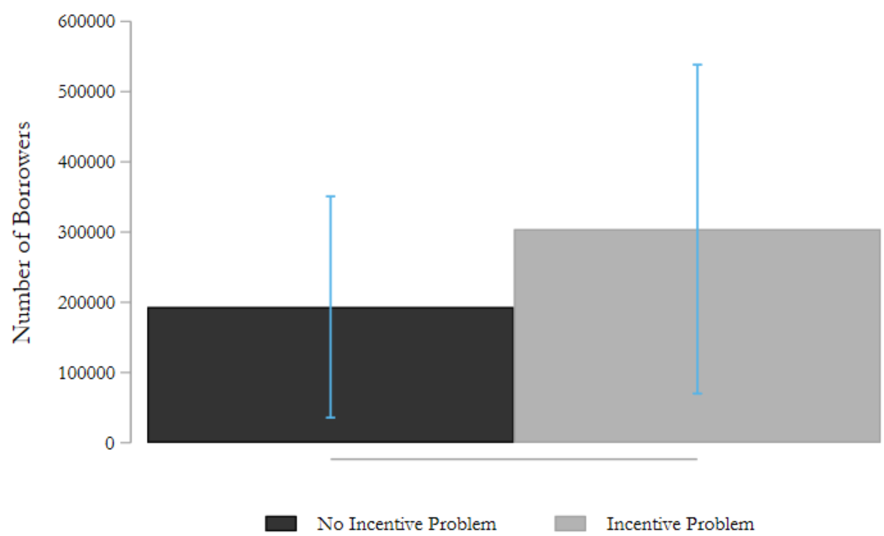
Figure 4: Distribution of Correlation between Baseline Recommendation and Default



Notes: Each observation in the above graph corresponds to a single loan officer's referrals. The x-axis corresponds to the loan officer's intrinsic motivation θ, as proxied by the (negative of the) correlation between their baseline referrals and borrowers' subsequent default, so that more intrinsically motivated loan officers are plotted farther to the right. The y-axis plots the (negative of the) correlation between the loan officer's referrals in the fixed-price or revenue-sharing survey round and a borrower's subsequent default, so that the more accurate a loan officer's referrals the higher the observation appears on the y-axis. Fixed-price referrals are plotted in red, and revenue-sharing referrals are plotted in blue. The dots correspond to a bin-scatter partitioning the loan officers into 15 bins, plotting the average x- and y-values for loan officers in the bin.

Figure 5: Portfolio Size and Total Borrowers by Whether MFI Exhibits Incentive Problem





Notes: This figure reports the portfolio size (in millions of 2023 USD) and the number of borrowers for MFIs with and without the incentive problem. The incentive problem is defined as meeting 4 criteria: that the MFI has an internal graduation program, that distinct loan officers manage the microcredit and graduation portfolio, that microcredit loan officers are compensated based on the size and/or repayment rate in their portfolio, and that microcredit loan officers do not receive any special bonus when their borrowers graduate out of microcredit. The primary data collection identified 15 MFIs that exhibit the incentive problem and 16 that did not. These are represented in the figure. The remaining 15 organizations that answered the survey did not have an internal graduation program. They are omitted from the figure.

Online Appendix for

Intrinsic Motivation and Referrals Within Firms: Evidence from a Large Microfinance Institution

Natalia Rigol and Benjamin N. Roth

A Online Appendix Tables and Figures

Table A1: Randomization Check

	All Borrowers	Control (Pre Fixed-Price) Sample	Treatment Sample
	Mean	Mean	Difference from Control Sample
	(1)	(2)	(3)
Panel A: Borrower Characteristics			
Age	46.324	46.411	-0.174
	[13.058]	[13.120]	(0.310)
Gender: Male	0.195	0.193	0.005
	[0.396]	[0.395]	(0.010)
Married	0.416	0.418	-0.004
	[0.493]	[0.493]	(0.012)
HH Size	3.667	3.660	0.014
	[1.593]	[1.599]	(0.048)
Education: Secondary and Above	0.639	0.638	0.001
	[0.480]	[0.480]	(0.011)
No. of Non-HH Workers	0.122	0.132	-0.019
	[1.022]	[1.107]	(0.012)
Sector: Manufacturing	0.288	0.287	0.002
	[0.453]	[0.453]	(0.007)
Sector: Retail	0.584	0.586	-0.003
	[0.493]	[0.493]	(0.009)
Sector: Services	0.123	0.123	0.002
	[0.329]	[0.328]	(0.006)
Sector: Agriculture	0.004	0.004	-0.001
	[0.064]	[0.067]	(0.001)
Monthly Business Revenues (USD)	1055.504	1058.685	-6.315
	[764.549]	[763.123]	(24.521)
Monthly Business Profits (USD)	703.966	703.103	1.712
	[519.045]	[521.888]	(17.570)
Group Size	21.715	21.662	0.106
	[2.726]	[2.629]	(0.170)
Borrower Cycle	8.409	8.595	-0.373
	[7.188]	[7.280]	(0.365)
Amount Borrowed	898.711	915.038	-33.137
	[529.621]	[534.299]	(20.796)
Days Late	0.083	0.087	-0.008
	[1.419]	[1.590]	(0.040)
Amount Late	0.956	0.817	0.283
	[11.475]	[9.364]	(0.315)
P-Value for Joint Difference F test:			0.802
Observations	46,797	23,475	46,797
Number of Borrowers	341.585	344.957	-6.772
	[76.381]	[74.377]	(10.109)
Portfolio (USD)	276529.031	283918.469	-14843.721
	[89986.625]	[88034.508]	(11880.571)
Total Amount Late (USD)	800.196	921.410	-243.490
	[1388.681]	[1628.729]	(182.922)
Fraction of Borrowers in Portfolio Endorsed at Baseline	0.061	0.065	-0.009
	[0.072]	[0.084]	(0.009)
Percent of Borrowers that Graduated	0.016	0.016	-0.001
	[0.013]	[0.012]	(0.002)
Tenure at MFI (in years)	9.472	9.286	0.379
	[3.236]	[3.154]	(0.467)
College Educated	0.363	0.408	-0.092
	[0.482]	[0.494]	(0.069)
Age	37.978	37.569	0.831
	[5.626]	[5.440]	(0.811)
Social Worker	0.803	0.816	-0.027
	[0.399]	[0.389]	(0.058)
P-Value for Joint Difference F test:			0.419
Observations	241	123	241

Notes: Column (1) reports average borrower and loan officer characteristics as of the 1st of November 2018, for *all* borrowers who had a loan with our partner lender and were evaluated by their officers during that month. Column (2) limits the sample and reports average borrower and loan officer characteristics only for loan officers who were selected to be surveyed in the Pre Fixed Price survey round in February 2019. We label these officers as our "Control Sample". Columns (1) and (2) report standard deviations in brackets. Column (3) reports the mean difference in borrower and loan officer characteristics of loan officers who were not assigned to submit endorsements in the Pre Fixed Price survey (We label these officers as our "Treatment Sample"), from those who were assigned to Control Sample. Column (3) reports standard errors in parentheses, clustered at the loan officer level.

Table A2: Impact of the Compensation Change on Total Cumulative Referrals

	Total Cumulative Referrals					
	Between Officers		All Officers		All Officers	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1: Post Fixed-Price	1.123***	1.232*	1.333***	1.560***	1.306***	1.528***
	(0.292)	(0.627)	(0.270)	(0.499)	(0.278)	(0.539)
β_2: Post Revenue-Share					2.129***	2.392***
					(0.338)	(0.679)
γ_1: Number of LO's that joined in the same period	-0.385*	-0.445*	-0.107	-0.156	-0.064	-0.140
	(0.212)	(0.230)	(0.205)	(0.198)	(0.254)	(0.254)
γ_2: Years in MFI	-0.017	0.017	-0.051	0.008	-0.065	0.015
	(0.044)	(0.045)	(0.057)	(0.057)	(0.078)	(0.071)
γ_3: Post Fixed-Price $\times$ LO's that joined in the same period		0.085		0.058		0.129
		(0.183)		(0.158)		(0.181)
γ_4: Post Fixed-Price $\times$ Years in MFI		-0.063		-0.084		-0.113
		(0.084)		(0.068)		(0.079)
γ_5: Post Revenue-Share $\times$ LO's that joined in the same period						0.032
						(0.214)
γ_6: Post Revenue-Share $\times$ Years in MFI						-0.084
						(0.101)
Mean: Referrals Pre Fixed-Price	0.19	0.19	0.19	0.19	0.19	0.19
	[0.86]	[0.86]	[0.86]	[0.86]	[0.86]	[0.86]
Mean: Referrals at Baseline	19.42	19.42	19.77	19.77	19.78	19.78
	[26.70]	[26.70]	[28.21]	[28.21]	[27.83]	[27.83]
Branch FE	X	X	X	X	X	X
Loan Officer Controls	X	X	X	X	X	X
Number of Loan Officers	241	241	241	241	241	241
Observations	241	241	364	364	592	592

Notes: **Specification**: Columns (1)-(2) implement Specification 5, Columns (3)-(4) implement Specification 7, Columns (5)-(6) implement Specification 8. Standard errors are in parentheses. Columns (1) - (4) only include the February (pre Fixed-Price) and March (post Fixed-Price) survey waves, with the former being the omitted group. In columns (1) and (2), there are 123 officers randomized to pre Fixed-Price and 118 officers randomized to *only* post Fixed-Price for between officer regression. Columns (3) and (4) include 246 observations from 123 officers observed twice in the pre and post Fixed-Price rounds, and 118 officers who are only observed once post Fixed-Price as a part of pooled regression. Columns (5) and (6) include the round in February, the round in March, and the round in April (post Revenue-Share), in which we collected referrals from 228 loan officers. Pre Fixed-Price is the omitted group. All regressions include branch fixed effects, loan officer controls (the total number of referrals made in November, size of total loan portfolio in November 2018, and number of borrowers in the loan officer's portfolio in November 2018), and standard errors clustered at the loan officer level. The odd columns include a control for the number of loan officers that joined the MFI in the same 6-month window as loan officer i and a control for the number of years the loan officer has worked at the MFI. The even columns also include the interaction of these two control variables and the indicators for the survey being Post Fixed Price and the survey being Post Revenue share. **Outcome variable**: Columns (1)-(8) report results on the total cumulative number of referrals made by a loan officer by each survey round.

Table A3: Does the Strength of Referrals Predict Default on Graduation Loans in the Short Run?

	Late $\geq$ 15 days		Late $\geq$ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Referrals								
$\beta_{Baseline3}$: Confidence 1-3	-0.008	-0.004	-0.015	-0.013	-0.032	-0.030	-15.056	-15.056
	(0.029)	(0.027)	(0.014)	(0.014)	(0.032)	(0.032)	(114.549)	(114.225)
$\beta_{Baseline4}$: Confidence 4	-0.013	-0.007	-0.002	0.000	0.026	0.028	56.769	56.769
	(0.031)	(0.030)	(0.017)	(0.017)	(0.050)	(0.050)	(106.618)	(106.316)
$\beta_{Baseline5}$: Confidence 5	-0.002	0.000	-0.014	-0.012	-0.017	-0.015	-51.109	-51.109
	(0.019)	(0.018)	(0.009)	(0.009)	(0.023)	(0.022)	(43.585)	(43.462)
Mean: Not Referred	0.077	0.077	0.031	0.031	0.062	0.062	128.547	128.547
	[0.266]	[0.266]	[0.174]	[0.174]	[0.242]	[0.242]	[544.687]	[544.687]
Number of Borrowers	708	708	708	708	708	708	708	708
Observations	26693	26693	26693	26693	708	708	708	708
Panel D: Fixed-Price or Revenue-Share Referrals								
$\beta_{FP\vee RS3}$: Confidence 1-3	-0.041**	-0.034*	-0.016**	-0.015*	-0.022***	-0.023***	-49.151***	-49.397***
	(0.018)	(0.019)	(0.008)	(0.008)	(0.007)	(0.007)	(17.989)	(17.993)
$\beta_{FP\vee RS4}$: Confidence 4	-0.002	-0.002	-0.016***	-0.016***	-0.022***	-0.023***	-49.151***	-49.397***
	(0.043)	(0.043)	(0.006)	(0.006)	(0.007)	(0.007)	(17.989)	(17.993)
$\beta_{FP\vee RS5}$: Confidence 5	-0.022	-0.023	-0.014**	-0.014**	-0.022***	-0.023***	-49.151***	-49.397***
	(0.030)	(0.030)	(0.006)	(0.006)	(0.007)	(0.007)	(17.989)	(17.993)
Mean: Not Referred	0.051	0.051	0.015	0.015	0.022	0.022	49.151	49.151
	[0.221]	[0.221]	[0.121]	[0.121]	[0.148]	[0.148]	[359.420]	[359.420]
Number of Borrowers	426	426	426	426	426	426	426	426
Observations	13691	13691	13691	13691	426	426	426	426
LASSO Controls		X		X		X		X

Notes: **Specification**: This table implements Specification 10. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. The regressors in each panel are dummies for the level of confidence (on a scale of 1 to 5, where 5 is very confident) the loan officer has in the quality of the borrower referred in that particular round. Due to a low number of observations, we combine confidence levels 1, 2, and 3. These dummies take a value of 0 if the borrower is not referred. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower level regressions. For all panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Fixed-Price or Revenue-Share are excluded from Panel A. Borrowers referred at Baseline or Revenue-Share are excluded from Panel B. Borrowers referred at Baseline or Fixed-Price are excluded from Panel C. Only borrowers referred at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never referred at any round. The sample in each panel is limited to graduation loans that are disbursed after the respective survey. So Panel A includes graduation loans made after December 2018, Panel B and D includes loans made after March 9, 2019, Panel C includes loans made after April 6, 2019 Data utilized comes from repayment reports between November 1, 2018 and March 1, 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a Graduation loan in the months after each referral wave, up to March 1, 2020. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a Graduation loan in the months after each referral wave, up to March 1, 2020. Columns (5)-(6) report results on an indicator variable for whether the borrower defaulted on a Graduation loan in the months after each referral wave, up to March 1, 2020. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each referral wave, up to March 1, 2020.

Table A4: Repayment Behavior of Groups in Which Someone Graduated

	Late $\geq$ 15 Days		Late $\geq$ 90 Days	
	(1)	(2)	(3)	(4)
Panel A: Never Referred				
β_{Never1}: Post 1 Grad	0.008	0.008	0.001	0.001
	(0.008)	(0.007)	(0.001)	(0.001)
β_{Never2}: Post 2 Grads	-0.006	-0.008	-0.002	-0.001
	(0.006)	(0.007)	(0.002)	(0.001)
β_{Never3}: Post 3 Grads	-0.011	-0.003	-0.000	0.000
	(0.007)	(0.002)	(0.000)	(0.000)
Mean: Pre-Period	0.027	0.027	0.008	0.008
	[0.162]	[0.162]	[0.090]	[0.090]
Number of Borrowers	2461	2461	2461	2461
Observations	86005	86005	86005	86005
Panel B: Referred at Baseline				
$\beta_{Baseline1}$: Post 1 Grad	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
$\beta_{Baseline2}$: Post 2 Grads	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
$\beta_{Baseline3}$: Post 3 Grads	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Mean: Pre-Period	0.100	0.100	0.033	0.033
	[0.300]	[0.300]	[0.180]	[0.180]
Number of Borrowers	717	717	717	717
Observations	19434	19434	19434	19434
Panel C: Referred at Fixed-Price or at Revenue-Share				
$\beta_{FP\vee RS1}$: Post 1 Grad	-0.006	-0.004	0.000	0.000
	(0.007)	(0.004)	(.)	(.)
$\beta_{FP\vee RS2}$: Post 2 Grads	0.009	0.007	0.000	0.000
	(0.010)	(0.007)	(.)	(.)
$\beta_{FP\vee RS3}$: Post 3 Grads	-0.023***	-0.004	0.000	0.000
	(0.007)	(0.005)	(.)	(.)
Mean: Pre-Period	0.155	0.155	0.052	0.052
	[0.362]	[0.362]	[0.222]	[0.222]
Number of Borrowers	507	507	507	507
Observations	9820	9820	9820	9820
LASSO Controls		X		X

Notes: **Specification**: This table implements Specification 15. Standard errors are in parentheses, clustered at the joint-liability (JL) group level. Standard deviations are in brackets. These are borrower-week level regressions, including loan cycle, month and individual fixed effects for all specifications. The sample is limited to groups where just one borrower graduated to a Graduation loan, and restricted to borrowers that were in the JL group when the graduating borrower left. The explanatory variables Post 1 Grad Post 2 Grads Post 3 Grads are dummy variables that equal 1 for periods when 1, 2, or 3 graduating borrowers have graduated and left the group, respectively, and zero when the borrowers are still a member of the JL group. Even columns include controls selected via double-post lasso using variables from Table A1. Note that the zeros in Panels B and C (variable drops) are caused by no one defaulting in those samples. **Outcome variable**: Columns (1) and (2) report results on a dummy variable that equals 1 if the borrower is 15 or more days late in their installments, and zero otherwise; Columns (3) and (4) reports results on a dummy variable that equals 1 if the borrower is 90 or more days late in their installments, and zero otherwise.

Table A5: Interaction between contract structure and intrinsic motivation using 15 day lateness prediction

	15 Days		90 Days		Defaulted		Amount	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fixed-Price Referrals								
β_{FP}: IM LO	0.010***		0.001***		0.021***		4.856	
	(0.002)		(0.000)		(0.006)		(3.173)	
γ_{FP}: Referred	-0.004	-0.001	-0.001**	0.000	0.004	0.012	-2.121	-1.126
	(0.004)	(0.004)	(0.000)	(0.000)	(0.015)	(0.015)	(6.475)	(5.244)
δ_{FP}: IM LO × Referred	-0.007	-0.007	-0.001	-0.002**	-0.052***	-0.052***	-14.650**	-14.510**
	(0.006)	(0.006)	(0.001)	(0.001)	(0.016)	(0.018)	(6.913)	(6.306)
Mean: Not Referred	0.012	0.012	0.002	0.002	0.027	0.027	11.916	11.916
	[0.107]	[0.107]	[0.039]	[0.039]	[0.162]	[0.162]	[100.367]	[100.367]
Number of Borrowers	50355	50355	50355	50355	50355	50355	50355	50355
Observations	2236536	2236536	2236536	2236536	50355	50355	50355	50355
Panel B: Revenue-Sharing Referrals								
β_{RS}: IM LO	0.010***		0.001***		0.021***		4.856	
	(0.002)		(0.000)		(0.006)		(3.173)	
γ_{RS}: Referred	-0.011***	-0.008**	-0.002***	-0.001**	-0.027***	-0.024***	-11.916***	-9.194***
	(0.002)	(0.003)	(0.000)	(0.001)	(0.004)	(0.009)	(2.051)	(3.237)
δ_{RS}: IM LO × Referred	-0.010***	-0.007	-0.001***	-0.002	-0.021***	-0.013	-4.856	-1.134
	(0.003)	(0.008)	(0.000)	(0.002)	(0.006)	(0.020)	(3.173)	(5.386)
Mean: Not Referred	0.012	0.012	0.002	0.002	0.027	0.027	11.916	11.916
	[0.107]	[0.107]	[0.039]	[0.039]	[0.162]	[0.162]	[100.367]	[100.367]
Number of Borrowers	50238	50238	50238	50238	50238	50238	50238	50238
Observations	2231296	2231296	2231296	2231296	50238	50238	50238	50238
LASSO Controls		X		X		X		X
Loan Officer FE		X		X		X		X
p-value for F test:								
$\gamma_{FP} = \gamma_{RS}$	0.076	0.112	0.095	0.132	0.040	0.028	0.130	0.117
$\delta_{FP} = \delta_{RS}$	0.664	0.992	0.914	0.921	0.040	0.143	0.130	0.075

Notes: **Specification**: This table implements Specification 12. Standard errors are in parentheses, clustered at the joint-liability (JL) group level. Standard deviations are in brackets. The regressors are a dummy variable for whether the loan officer is intrinsically motivated, whether a borrower is referred in after the implementation of the Fixed-Price (Panel A) or Revenue-Share (Panel B) contracts, and the interaction between these two variables. Relative to table 4, a loan officer is intrinsically motivated if she scored below the median when we estimate the correlation between whether they referred a borrower at baseline and the likelihood that the borrower subsequently was at least 15 days late in the microcredit portfolio. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower level regressions. For both panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Revenue-Share and Baseline are excluded from Panel A. Borrowers referred at Fixed-Price and Baseline are excluded from Panel B. The omitted group in all panels is borrowers who were never referred at any round. The sample in both panels is limited to joint-liability loans that are active during the intervention period (Feb 22, 2019 to Apr 6, 2019) and those made after the intervention period until March 1, 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a loan. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a loan. Columns (5)-(6) report results on an indicator variable for defaulted on a loan. Columns (7)-(8) report results on total amount defaulted.

Table A6: Interaction between contract structure and intrinsic motivation using 90 day lateness prediction

	15 Days		90 Days		Defaulted		Amount	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fixed-Price Referrals								
β_{FP}: IM LO	0.007**		0.001**		0.018**		0.449	
	(0.003)		(0.001)		(0.009)		(4.176)	
γ_{FP}: Referred	-0.006	0.000	-0.001	0.000	-0.017	-0.003	-9.434	-6.183
	(0.004)	(0.004)	(0.001)	(0.001)	(0.013)	(0.014)	(6.430)	(5.309)
δ_{FP}: IM LO × Referred	-0.013*	-0.014*	-0.003***	-0.003***	-0.040***	-0.044**	-8.821	-12.328*
	(0.007)	(0.007)	(0.001)	(0.001)	(0.015)	(0.020)	(7.046)	(7.200)
Mean: Not Referred	0.017	0.017	0.002	0.002	0.040	0.040	17.806	17.806
	[0.129]	[0.129]	[0.048]	[0.048]	[0.195]	[0.195]	[121.207]	[121.207]
Number of Borrowers	36725	36725	36725	36725	36725	36725	36725	36725
Observations	1613081	1613081	1613081	1613081	36725	36725	36725	36725
Panel B: Revenue-Sharing Referrals								
β_{RS}: IM LO	0.007**		0.001**		0.018**		0.449	
	(0.003)		(0.001)		(0.009)		(4.176)	
γ_{RS}: Referred	-0.018***	-0.015***	-0.003***	-0.002***	-0.040***	-0.044***	-17.806***	-14.557**
	(0.003)	(0.005)	(0.000)	(0.001)	(0.005)	(0.017)	(3.022)	(6.481)
δ_{RS}: IM LO × Referred	-0.007	-0.001	-0.001**	-0.001	-0.018**	0.013	-0.449	5.542
	(0.004)	(0.009)	(0.001)	(0.002)	(0.009)	(0.024)	(4.176)	(7.596)
Mean: Not Referred	0.017	0.017	0.002	0.002	0.040	0.040	17.806	17.806
	[0.129]	[0.129]	[0.048]	[0.048]	[0.195]	[0.195]	[121.207]	[121.207]
Number of Borrowers	36616	36616	36616	36616	36616	36616	36616	36616
Observations	1608353	1608353	1608353	1608353	36616	36616	36616	36616
LASSO Controls		X		X		X		X
Loan Officer FE		X		X		X		X
p-value for F test:								
$\gamma_{FP} = \gamma_{RS}$	0.010	0.011	0.047	0.028	0.079	0.040	0.171	0.210
$\delta_{FP} = \delta_{RS}$	0.391	0.228	0.110	0.283	0.079	0.051	0.171	0.049

Notes: **Specification**: This table implements Specification 12. Standard errors are in parentheses, clustered at the joint-liability (JL) group level. Standard deviations are in brackets. The regressors are a dummy variable for whether the loan officer is intrinsically motivated, whether a borrower is referred in after the implementation of the Fixed-Price (Panel A) or Revenue-Share (Panel B) contracts, and the interaction between these two variables. Relative to table 4, a loan officer is intrinsically motivated if she scored below the median when we estimate the correlation between whether they referred a borrower at baseline and the likelihood that the borrower subsequently was at least 90 days late in the microcredit portfolio. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower level regressions. For both panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Revenue-Share and Baseline are excluded from Panel A. Borrowers referred at Fixed-Price and Baseline are excluded from Panel B. The omitted group in all panels is borrowers who were never referred at any round. The sample in both panels is limited to joint-liability loans that are active during the intervention period (Feb 22, 2019 to Apr 6, 2019) and those made after the intervention period until March 1, 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a loan. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a loan. Columns (5)-(6) report results on an indicator variable for defaulted on a loan. Columns (7)-(8) report results on total amount defaulted.

Table A7: Interaction between contract structure and intrinsic motivation using amount defaulted prediction

	15 Days		90 Days		Defaulted		Amount	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fixed-Price Referrals								
β_{FP}: IM LO	0.006**		0.001*		0.013*		4.341	
	(0.003)		(0.000)		(0.007)		(3.672)	
γ_{FP}: Referred	-0.006	-0.005	-0.002***	-0.001	-0.021*	-0.020	-5.834	-8.181
	(0.004)	(0.004)	(0.000)	(0.001)	(0.012)	(0.013)	(6.763)	(5.868)
δ_{FP}: IM LO × Referred	-0.004	0.002	0.000	0.000	-0.017	0.001	-12.392*	-3.984
	(0.007)	(0.007)	(0.001)	(0.001)	(0.017)	(0.020)	(7.339)	(6.760)
Mean: Not Referred	0.015	0.015	0.002	0.002	0.037	0.037	14.555	14.555
	[0.120]	[0.120]	[0.047]	[0.047]	[0.189]	[0.189]	[106.577]	[106.577]
Number of Borrowers	43420	43420	43420	43420	43420	43420	43420	43420
Observations	1921612	1921612	1921612	1921612	43420	43420	43420	43420
Panel B: Revenue-Sharing Referrals								
β_{RS}: IM LO	0.006**		0.001		0.013*		4.341	
	(0.003)		(0.000)		(0.007)		(3.672)	
γ_{RS}: Referred	-0.016***	-0.013**	-0.002***	-0.002*	-0.037***	-0.031**	-14.555***	-9.086**
	(0.002)	(0.006)	(0.000)	(0.001)	(0.005)	(0.015)	(2.400)	(4.288)
δ_{RS}: IM LO × Referred	-0.002	0.002	-0.000	0.001	-0.013*	-0.000	-4.341	-1.485
	(0.004)	(0.007)	(0.001)	(0.001)	(0.007)	(0.018)	(3.672)	(5.437)
Mean: Not Referred	0.015	0.015	0.002	0.002	0.037	0.037	14.555	14.555
	[0.120]	[0.120]	[0.047]	[0.047]	[0.189]	[0.189]	[106.577]	[106.577]
Number of Borrowers	43325	43325	43325	43325	43325	43325	43325	43325
Observations	1917319	1917319	1917319	1917319	43325	43325	43325	43325
LASSO Controls		X		X		X		X
Loan Officer FE		X		X		X		X
p-value for F test:								
$\gamma_{FP} = \gamma_{RS}$	0.020	0.222	0.091	0.374	0.153	0.506	0.193	.
$\delta_{FP} = \delta_{RS}$	0.772	0.986	0.735	0.757	0.775	0.944	0.231	.

Notes: **Specification**: This table implements Specification 12. Standard errors are in parentheses, clustered at the joint-liability (JL) group level. Standard deviations are in brackets. The regressors are a dummy variable for whether the loan officer is intrinsically motivated, whether a borrower is referred in after the implementation of the Fixed-Price (Panel A) or Revenue-Share (Panel B) contracts, and the interaction between these two variables. Relative to table 4, a loan officer is intrinsically motivated if she scored below the median when we estimate the correlation between whether they referred a borrower at baseline and the likelihood that the amount that the borrower subsequently defaulted on in the microcredit portfolio. Columns (1)-(4) are borrower-week level regressions and include fixed effects for the month in which the loan is due. Columns (5)-(8) are borrower level regressions. For both panels, referred borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers referred at that given round and those never referred. So borrowers referred at Revenue-Share and Baseline are excluded from Panel A. Borrowers referred at Fixed-Price and Baseline are excluded from Panel B. The omitted group in all panels is borrowers who were never referred at any round. The sample in both panels is limited to joint-liability loans that are active during the intervention period (Feb 22, 2019 to Apr 6, 2019) and those made after the intervention period until March 1, 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls in Panel A of Table A1. Tests of equality of Baseline and Post Fixed-Price, Baseline and Post Revenue-Share, and Post Fixed-Price and Post Revenue-Share coefficients are based on the SURS framework. **Outcome variable**: Columns (1)-(2) report results on an indicator variable for being late 15 or more days on a loan. Columns (3)-(4) report results on an indicator variable for being late 90 or more days on a loan. Columns (5)-(6) report results on an indicator variable for defaulted on a loan. Columns (7)-(8) report results on total amount defaulted.

Table A8: Comparison of Sample MFIs with MFIs in MIX Data

	Sample MFIs	Mix Data MFIs	Difference between Sample and Mix data MFIs
	Mean	Mean	Mean differences
	(1)	(2)	(3)
Panel A: All Countries			
Total Borrowers	220900.25	45972.47	107960.53*
	[321204.16]	[152211.25]	(55280.09)
Observations	41	2,699	2,740
Portfolio Size (Millions of USD)	249.14	57.08	146.04*
	[439.14]	[207.91]	(83.45)
Observations	42	3,027	3,069
Panel B: Only Countries Represented in Sample			
Total Borrowers	220900.25	88341.17	75905.75
	[321204.16]	[218078.56]	(56612.99)
Observations	41	720	761
Portfolio Size (Millions of USD)	249.14	111.76	97.16
	[439.14]	[295.81]	(84.39)
Observations	42	792	834

Notes: This table shows the mean difference in characteristics between our sample and MIX data. In Panel A, the sample is all the MFIs represented in the MIX dataset (3114) for which the characteristics data is available. In Panel B, the sample is limited to MFIs located in countries represented in our primary survey sample (809 MFIs in 15 countries) for which the characteristics data is available. Column (1) displays average characteristics of the 46 MFIs that responded the primary survey collected by the authors. We are able to match 30 of the 46 institutions in MIX. For these 30, we use characteristics in the MIX dataset. For another 12 institutions in the primary survey sample, we obtain characteristics from representatives that answered the survey or from the company's financial statements. We do not have borrower or portfolio size information for 4 sample MFIs. Standard deviations are reported in brackets. Column (2) displays the difference in means between both samples, controlling for the year the data is collected in either dataset. Robust standard errors are reported in parentheses.

Table A9: Comparison of Sample MFIs with and without graduation program

	MFIs with graduation program	MFIs without graduation program	Difference between column 1 and column 2
	Mean	Mean	Mean differences
	(1)	(2)	(3)
Portfolio Size (Millions of USD)	111.86	36.42	75.44***
	[285.90]	[163.64]	(15.56)
Total Borrowers	87115.81	34407.45	52708.36***
	[210736.20]	[130641.40]	(11763.40)
Targets Very poor clients	0.26	0.24	0.02
	[0.44]	[0.43]	(0.04)
Targets Low income clients	0.69	0.67	0.02
	[0.46]	[0.47]	(0.04)
Report using a poverty measure	0.67	0.66	0.01
	[0.47]	[0.48]	(0.04)
Offers non-financial Enterprise services?	0.51	0.47	0.04
	[0.50]	[0.50]	(0.05)
Offers non-financial education services?	0.62	0.56	0.07
	[0.49]	[0.50]	(0.05)
Offers non-financial Women's empowerment services?	0.38	0.35	0.03
	[0.49]	[0.48]	(0.04)
Offers non-financial Health services?	0.19	0.15	0.04
	[0.40]	[0.36]	(0.03)
Region: Africa	0.32	0.25	0.07**
	[0.47]	[0.44]	(0.03)
Region: East Asia and the Pacific	0.14	0.13	0.01
	[0.34]	[0.34]	(0.02)
Region: Eastern Europe and Central Asia	0.22	0.19	0.03
	[0.42]	[0.39]	(0.03)
Region: Latin America and The Caribbean	0.15	0.29	-0.15***
	[0.35]	[0.46]	(0.03)
Region: Middle East and North Africa	0.04	0.04	-0.00
	[0.20]	[0.20]	(0.01)
Region: South Asia	0.13	0.09	0.04*
	[0.33]	[0.28]	(0.02)
Observations	468	410	878

Notes: This table shows the mean difference in characteristics between MFIs with graduation programs and without graduation programs. The sample is all the MFIs represented in the MIX dataset (3114) for which the characteristics data is available. Columns (1) and (2) show the mean MFI characteristics of the MIX data set with and without graduation programs, respectively. Standard deviations are reported in brackets. Robust standard errors are reported in parentheses.

Figure A1: Instructions For First Round (Baseline) of Recommendations

23rd November, 2018

Dear Branch Manager,

As you are aware, over the past several years, **[Lender’s Name Redacted]** has made significant strides in developing the **[Product Name Redacted]** product to help our borrowers continue to improve their livelihoods. Your efforts and those of the loan officers have been integral in the process of assessing which borrowers are ready to switch from group to individual liability loans. We are grateful for all your help in making this initiative a reality. We know, however, that this process can be cumbersome to you and your loan officers. We are now taking the next steps in making recommendations as easy and speedy as possible for branches so that you can continue to focus your attention on bettering the welfare of our borrowers.

[Lender’s Name Redacted] has worked with a consultancy in order to design a streamlined process of borrower recommendations for **[Product Name Redacted]**. In this effort, **[Lender’s Name Redacted]** has created a loan officer-specific form that would allow loan officers to more easily provide their recommendations. We would like each loan officer to comment on which borrowers from their groups (if any) should be considered for **[Product Name Redacted]**. This is exactly the same process that we have utilized at **[Lender’s Name Redacted]** for the past few years to make recommendations, but we are trying to formalize this process.

This form will be delivered by a courier tomorrow at **[XX]** am/pm. The loan officers should carefully read the instructions in the package, complete the recommendations, and return a sealed envelope (which will be provided) to the courier.

There are a few things that we would like you to keep in mind for this process:

1. Loan officers should use the standard criteria that they have utilized in the past to make recommendations as to which borrowers should be eligible for **[Product Name Redacted]**.

2. Loan officers do not have to provide at least one recommendation per group. If there is no one in the group who they think should be eligible, they should not recommend anyone.

3. Loan officers can make multiple recommendations from the same group.

4. As in the past, making a recommendation of a particular borrower does not guarantee that the borrower will receive the **[Product Name Redacted]** loan as they will have to go through the standard screening process. Making a recommendation also does not force a borrower to take the **[Product Name Redacted]** loan if they prefer to keep a **[Product Name Redacted]**.

5. Please ensure that once the courier arrives and distributes the recommendation forms, loan officers sit individually to complete the form. The form should take between 10-20 minutes to complete.

6. The courier that arrives with the packages is trained to answer basic questions about how to fill out the form and how to submit recommendations.

7. Two example recommendation forms have been attached here for your reference. Example Form 1 shows how to recommend borrowers. Example Form 2 shows that to do if the loan officer has no one to recommend in a particular group.

8. If any piece of the form is missing (all materials will be enumerated) or there are errors in the form, please contact **[Redacted]**.

Thank you for your cooperation in this process.

[Redacted]

Figure A2: First Round (Baseline) Survey Template

EXAMPLE SURVEY FOR COLLECTING BORROWER REFERRALS

In an effort to formalize the screening process for individual liability loans, [Lender's Name Redacted] would like each loan officer to comment on which borrowers (if any) from their borrowing groups should be considered for the individual loan product.

Which borrowers will be a good fit for the individual liability loan product?
- If you want to recommend someone, check the box against their name.
- If you do no wish to recommend someone, please leave the box blank.
- It's okay to say no one is a good fit. If so, please check the box at the bottom of the page which states that you are not making any recommendations from this group.

If recommended, please tell us how strongly you recommend this borrower:
1 = Very weakly, 2 = Somewhat weakly, 3 = Neither weakly nor strongly, 4 = Somewhat strongly, 5 = Very strongly

Borrower Name:	
Borrowing Group Name:	
Borrowing Group ID:	

Borrower ID	Borrower Name	Check if you want to recommend a borrower	How strongly do you recommend this borrower?
1	Person A	☐ Check	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
2	Person B	☐ Check	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
3	Person C	☐ Check	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
4	Person D	☐ Check	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
5	Person E	☐ Check	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

If you have not selected anyone from this borrowing group, please confirm by checking the box	☐ Did not recommended anyone

Figure A3: MFIs Responding to Our Survey of Management Practices

	Microfinance Institution Name	Country
1	BancoSol	Bolivia
2	Crecer Bolivia	Bolivia
3	Centro de Apoio aos Pequenos Empreendimentos	Brazil
4	Associação Mineira de Crédito Popular	Brazil
5	Instituição Comunitaria de Crédito Conquista	Brazil
6	Icc itabuna Solidaria	Brazil
7	Associação Brasileira para o desenvolvimento da Família- Banco da Família	Brazil
8	Crediamai Agencia de Microcredito	Brazil
9	Instituição de Crédito Solidário - CREDISOL	Brazil
10	Acredite Associação de Microcrédito Alto Vale do Itajaí	Brazil
11	Fundación Santo Domingo	Colombia
12	Corporación de Crédito Contactar	Colombia
13	Mibanco Colombia	Colombia
14	Banco Ademi	Dominican Republic
15	Banco Pichincha	Ecuador
16	BanEcuador	Ecuador
17	Tamweely microfinance	Egypt
18	Fundacion Genesis Empresarial	Guatemala
19	Banco Popular SA	Honduras
20	Dvara Kshetriya Gramin Financial Services Private Limited	India
21	Janakalyan Financial Services Private Limited	India
22	Svasti Microfinance Private Limited	India
23	Chaitanya India Fin Credit Pvt Ltd	India
24	Nabfins Ltd	India
25	Wesghats Microfinance Ltd	India
26	Unacco Financial	India
27	Valar Aditi Social Finance Private Limited	India
28	Muthoot Microfin Limited	India
29	Sub-K Impact Solutions Ltd	India
30	Sanghamitra MFI	India
31	Vitas Jordan	Jordan
32	Faulu Microfinance Bank	Kenya
33	Emprendedores Firme	Mexico
34	Financiera Braxel S.A. de C.V. SOFOM ENR	Mexico
35	Finsostener S.A. de C.V. SOFOM ENR	Mexico
36	Compartamos Banco	Mexico
37	Fortaliza a mi Futuro S.A. de C.V. SOFOM ENR	Mexico
38	Crediavance Financiera	Mexico
39	AMEXTRA SOFINCO S.A. de C.V. SOFOM ENR	Mexico
40	Emprendamis Fin	Mexico
41	Financiamiento Progresemos, S.A. de C.V. SOFOM ENR	Mexico
42	UNIMEX Financiera S.A. de C.V. SOFOM ENR	Mexico
43	Kapitalmujer S.A. de C.V. SOFOM ENR	Mexico
44	Fundación Paraguaya	Paraguay
45	Mibanco	Peru
46	Enda tamweel	Tunisia

B Spillovers onto Joint-Liability Borrowers when Someone Graduates

The results thus far suggest that our partner lender benefited from graduating borrowers referred after the fixed-price and revenue-sharing contracts. However, one potential cost of graduating qualified borrowers, which so far we have not explored, is that there may be negative externalities on the joint-liability borrowers left behind by the borrowers who graduate. This could be the case if the best borrowers in the group provide advice, repayment discipline, or insurance to their groupmates. In this section we examine the repayment behavior in joint-liability groups before and after they lose a borrower to graduation and find no evidence of negative spillovers from graduation.

Specifically, for each survey round S, and for the population of all joint-liability borrowers who had a group member referred in survey round S graduate between survey round S and March 2020, we regress

$$y_{it} = \alpha + \sum_{n=1}^{3} \beta_{Sn} Post\ n\ Grads_{it} + \gamma X_i + \delta_i + \phi_t + \lambda_c + \epsilon_{it} \tag{15}$$

The level of observation is borrower by month. Here $Post\ n\ Grads_{it}$ is an indicator variable taking the value of 1 if n of borrower i's group mates have already graduated by month t and 0 else, y_{it} is a measure of borrower i's repayment in month t, δ_i is a borrower fixed effect, λ_c is a loan cycle fixed effect, and all other variables are as defined above. The sample is restricted to joint-liability borrowers who were present both before and after a borrower in their group graduated, and standard errors are clustered at the borrower level.

This specification allows us to capture potential non-linearities in spillovers from groupmates graduating (e.g. perhaps little harm is conferred on the group when just one borrower graduates, but repayment deteriorates if at least two borrowers graduate). The coefficients β_{Sn} capture any reduction or improvement in the repayment behavior of joint-liability borrowers when n of their group mates who were referred in survey round S graduate. We note that we do not have random variation in whether a referred borrower graduates. However, our regression includes both month and loan cycle fixed effects, so β_{Sn} is unlikely to capture any secular trend. And at the time of our study, the process by which borrowers were selected to graduate was determined by a loan officer who specializes in graduation loans and had no responsibility or stake in the microcredit portfolio.

So reverse causality is unlikely to drive any observed relationships between borrower graduation and the repayment of her peers.

Results are presented in Table A4 for borrowers who graduated and were not referred in any survey round (Panel A), borrowers who graduated and were referred in baseline (Panel B), and borrowers who graduated and were referred after either the fixed-price or revenue-sharing contracts (Panel C). Across the board the point estimates are small, and we can never reject that there are no negative spillovers on the borrowers who are left behind in joint-liability groups. In many cases, point estimate are precisely 0. In these cases we cannot estimate the corresponding standard errors as there is no default among anyone in the corresponding joint-liability groups. We also cannot estimate these regressions on default and amount defaulted as there is no default in these groups across any of the panels.

C Formula for Computing Loan Officer Compensation

In this section we describe the formula by which the variable component of loan officer compensation, or bonus, was computed as of November 2018 (i.e. prior to our compensation shifts). Loan officer compensation was calculated and distributed monthly, as a function of the number of borrowers their portfolio, the total amount of capital in their portfolio, and various summaries of borrower lateness. The following steps document the exact calculation.

Step 1: Determining a Loan Officer's "Range"

Loan officers fall into one of three ranges, determined by the largest number of borrowers they have ever managed.

Range	Number of borrowers
1	0-168
2	169-350
3	$\geq$351

Step 2: Determining Whether a Loan Officer Has Access to Any Bonus

To receive a positive bonus, loan officers must meet the following three conditions.

- Condition 1: The loan officer must be in Range 2 or 3.
- Condition 2: If the loan officer is in Range 3, then either she must currently manage at least 351 borrowers, or the average number of borrowers she has managed over the last four months must be at least 351.
- Condition 3: Her three-month average portfolio at risk must not exceed 3%, where portfolio at risk in a given month is defined as $\frac{\text{Total debt of borrowers who are at least 7 days late}}{\text{Total value of portfolio}}$

Step 3: Determining The Base Bonus

If the loan officer meets all conditions in Step 2 above she is eligible for a positive bonus, which is a function of her Range and the total value of her portfolio in chilean pesos (CLP).

Step 4: Determining Compensation Multiplier Based on Lateness

Loan officers in Range 3 are eligible for a compensation multiplier as a function of their total portfolio at risk (defined in Step 2).

Level	Ranges	Portfolio	Bonus Amount (Base Bonus)
1	2 and 3	$\geq$ CLP$20,000,000	CLP$23,543
2	2 and 3	$\geq$ CLP$40,000,000	CLP$70,628
3	2 and 3	$\geq$ CLP$50,000,000	CLP$141,256
4	2 and 3	$\geq$ CLP$70,000,000	CLP$223,655
5	3	$\geq$ CLP$85,000,000	CLP$278,863
6	3	$\geq$ CLP$100,000,000	CLP$315,236
7	3	$\geq$ CLP$130,000,000	CLP$343,219

Portfolio at risk	Multiplier
0% - 0.49%	10%
0.5% - 0.99%	6%
1% - 1.49%	4%
1.5% - 1.99%	2%
$\geq$ 2%	-

A loan officer i's bonus is then Base Bonus$_i$ $*$ (1+multiplier$_i$), where Base Bonus$_i$ is computed in Step 3 and multiplier$_i$ is computed in Step 4.