Loan Officers Impede Graduation from Microcredit: Strategic Communication in a Large Microfinance Institution *

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Abstract

Graduating borrowers from microcredit to larger loans represents an important opportunity for increasing livelihoods. We demonstrate that loan officers impede borrower graduation due to common features of their compensation. We implement an experiment with 243 loan officers in which we change compensation and find that it causes loan officers to endorse more borrowers for graduation. Relative to those endorsed before the change, borrowers endorsed afterwards exhibit better repayment in graduation loans and their businesses grow more upon receiving graduation loans. Utilizing existing and novel survey data on the organizational practices of microfinance institutions around the world, we find that about half of all microfinance institutions have internal graduation programs and of these between 31% and 54% employ the same compensation practices as our partner lender. This suggests that loan officer incentives may be a significant deterrent to borrower graduation worldwide.

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1 Introduction

Once hailed for its potential to lift the world's poorest entrepreneurs out of poverty, microcredit has fallen short of its initial promise.[1] One promising route to increase its impact is to "graduate" borrowers from micro to larger loans, either within the same microfinance institutions (MFIs) or at formal banks (Bari et al., 2021; Bryan et al., 2022). Indeed, more than half of MFIs worldwide represented in the MIX Market dataset have internal graduation programs, whereby borrowers can move from micro to larger loans without moving to a new lending institution.[2] In this paper we document that common loan officers compensation practices induce an organizational obstacle to graduating borrowers from microcredit to larger loans.

Loan officers are often rewarded for maintaining a large borrower portfolio and high rates of repayment; 80% of MFIs represented in the MIX Market dataset use such monetary incentives.[3] These compensation schemes align the interests of loan officers with the profitability of their portfolio, but they also induce an implicit penalty when borrowers graduate out of their portfolio. In turn, loan officers may withhold discretionary support from borrowers when providing it would jeopardize the loan officer's compensation. However, the extent to which this limits graduation rates in practice is an empirical question.

We provide empirical evidence that these standard loan officer compensation practices create an important misalignment of interests between loan officers and their borrowers. And we demonstrate that reforming these compensation practices has the potential to increase graduation rates out of microcredit.

Specifically, we worked with one of Chile's largest microfinance institutions. In addition to standard, joint-liability microloans, our partner lender has an internal graduation program. Borrowers who graduate from the microcredit portfolio are offered larger, more flexible, individual-liability *graduation loans*. Importantly, at the time of our study, the

[1] In a review of six experiments that randomize access to microcredit, Banerjee et al. (2015) finds at best modest impacts of microcredit on business growth. Meager (2019) confirms this conclusion in a meta analysis of these six experiments and one more. In a longer-term followup Banerjee et al. (2019) finds a positive impact of microcredit on entrepreneurs with pre-existing businesses, and Breza and Kinnan (2021) finds positive impacts of microcredit in general equilibrium, suggesting the impact of microcredit may be positive for some entrepreneurs.

[2] This MIX Market data were collected annually from 2002 to 2017, surveying the management practices of over 3100 MFIs around the world. We define an MFI to have an internal graduation program if they report having both a "micro" loan and either an "SME" or "Large" loan.

[3] Moreover, these monetary incentives are quite significant. McKim and Hughart (2005) documents that they amount to 28% of total loan officer compensation on average.

loan officers who managed the joint-liability loans were entirely non-overlapping with the loan officers who managed the graduation loans. Loan officers were rewarded for the size and performance of their portfolio. Thus, even though the organization benefits when high-performing borrowers move from joint-liability to graduation loans, joint-liability loan officers suffered a pecuniary penalty from borrower graduation.

Our partner lender relies on loan officer endorsements as an input into the borrower graduation process. However, prior to our study, they received few endorsements from joint-liability loan officers about borrowers who were qualified to graduate. Our partner lender hypothesized this was due to a strategic communication problem whereby loan officers withheld endorsements of qualified borrowers to maintain high rates of compensation.

We implemented an experiment with our partner lender and its 243 loan officers to investigate this hypothesis. We introduced two compensation changes that reduced, and partially reversed the penalty that loan officers face when losing their borrowers. The first change, which we refer to as *Mitigation*, mitigated some of the implicit penalties that joint-liability officers incurred upon borrower graduation. Specifically, under Mitigation, loan officers were given a six month grace period during which time graduated borrowers were treated as if they were still part of the loan officer's portfolio for the purpose of determining compensation. The second change, which we refer to as *Recognition*, provided an additional reward (or recognition) for joint-liability loan officers when their borrowers graduated and performed well in the graduation loan. We also conducted several surveys eliciting endorsements from loan officers for borrowers who may be qualified for graduation loans. Our partner lender utilized these endorsements for graduation decisions, though not until after the completion of our study.

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 endorsement survey five days before anyone found out about the compensation change, and therefore their endorsements were influenced by the baseline compensation contract. Our treatment loan officers received their endorsement survey two days following the announcement of the Mitigation 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 endorsements between our treatment and control loan officers can be attributed to the compensation change. One month after the Mitigation contract was announced, all loan officers received news of a second change to their compensation contract – Recognition, and we conducted a final round of endorsements.[4]

This 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 manner in which they are compensated. So, randomizing the timing of surveys relative to firm-wide changes enables researchers to evaluate the causal impact of variety of managerial practices that are too sensitive to themselves be randomized.[5]

Our experiment confirms that pecuniary penalties for losing borrowers are a substantial deterrent to loan officer endorsements. Indeed, the compensation changes resulted in several hundred new endorsements for borrowers to graduate. These represent an 11% increase in endorsements relative to those we collected in our 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 change, however, is not the number of additional endorsements but rather the value of the additional endorsements in predicting borrower repayment behavior and business growth. Graduated borrowers endorsed after the compensation shift exhibit significantly better repayment than graduated borrowers endorsed prior to the compensation shift. Moreover, graduated borrowers endorsed after the shift experience about twice as much growth in their profits relative to borrowers endorsed prior to the shift. This suggests that, prior to the compensation shift, not only were loan officers strategically withholding endorsements of qualified borrowers, they were withholding endorsements of their *most qualified* borrowers. Indeed, borrowers endorsed after the compensation shift also exhibited better repayment in the joint-liability portfolio, which may explain loan officers' unwillingness to endorse them under the baseline compensation scheme.

To provide another view into the strategic behavior of loan officers before and during our experiment we utilize administrative data on loan officer compensation and borrower

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

[5]Bassi and Rasul (2017) employ a similar design to estimate the impact of a Papal visit to Brazil on people's beliefs about fertility. But to our knowledge ours is the first study to employ this experimental design within a firm to evaluate sensitive managerial practices.

characteristics. We identify a positive causal relationship between the cost of losing a borrower and the likelihood that a loan officer endorses her under the baseline compensation scheme. Notably, this relationship diminishes significantly after our intervention.

We operationalize the cost of losing a borrower in several ways. Our preferred method is to estimate a computationally tractable approximation of each borrower's *Shapley Value* – a notion from cooperative game theory that determines the portion of a loan officer's compensation attributable to each of her borrowers. To identify the causal impact of the cost of losing a borrower on the likelihood a loan officer endorses her, we exploit discontinuities in the formula by which loan officers are compensated. In effect, we compare the likelihood of endorsement for borrowers whose loan officers are far from a compensation threshold to that of borrowers whose loan officers are close to a compensation threshold, thereby isolating variation in the cost a loan officer faces of losing her borrowers. This allows us to circumvent the concern that borrowers who are costlier to lose (e.g. borrowers with larger loans) are often also more qualified for graduation. In our preferred estimate we find that, holding other borrower characteristics fixed, increasing the cost of losing a borrower by 1 standard deviation corresponds to a reduction in the likelihood of endorsement of 17% of the baseline endorsement probability. After our intervention, this effect diminishes such that increasing the cost of losing a borrower by 1 standard deviation corresponds to a reduction in the likelihood of endorsement of only 2% of the baseline endorsement probability, indicating that our intervention successfully diminished the incentive to strategically withhold endorsements.

How broadly do our results generalize beyond our partner lender? We conducted a survey of managers at 40 microfinance institutions in Latin America and India to assess their loan officer compensation practices. Of these institutions, 65% have internal graduation programs. Between 31% and 54% 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 the limited impact that microcredit has had on entrepreneurship and more broadly on borrower incomes. We discuss implications for policy in the conclusion.

Our results might also generalize to organizations beyond microfinance institutions. Our study can be viewed as providing evidence for frictions that inhibit the efficient allocation of human capital within organizations. For instance, the disincentive that loan officers face in graduating high-performing borrowers resembles the disincentive that managers face in promoting high-performing employees within and across organizations (e.g. Pei, 2016; Friebel and Raith, 2022; Haegele, 2022). And they similarly resemble the disincentives that Ph.D. advisors face in helping their students to graduate, within the disciplines in which students provide important inputs into the research of their supervisors.

Beyond the literature cited above, which explores the reasons underlying the low impact of microcredit, our analysis contributes to 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 literature, 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, 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 Egyptian 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.

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 an 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 the context, experimental design, and data. Section 3 documents that loan officers were withholding endorsements of qualified borrowers prior to our intervention. Section 4 demonstrates that borrowers endorsed after the compensation change exhibited better repayment in graduation loans and experienced more growth in business profits folowing graduation than those endorsed prior to the compensation change, indicating that loan officers had been withholding their most qualified borrowers prior to the compensation change. Section 5 examines the strategic determinants of loan officer endorsements. Section 6 presents results from our novel survey of microcredit managers around the world, establishing the broader applicability of our results, and Section 7 concludes.

2 Context, Experimental Design, and Data

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 loan product is a joint-liability group loan. Borrowers who are geographically proximate are divided into groups of about 22 people.

The mean joint-liability loan size is USD 860, the typical duration of a loan cycle is 4.5 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. Aside from being unable to borrow from the organization in the future, the loans of borrowers who are over 90 days late on repayments are sent to a collections agency and the central credit bureau (DICOM) is informed. These events, however, are rare. 2% of loans are 0-30 days late, 0.3% of loans are 30-60 days late, 0.2% of loans are 60-90 days late, and 0.1% of loans are over 90 days late.

While joint-liability loans constitute the majority of our partner's portfolio, they also offer a *graduation loan* product. Graduation loans are larger than the joint-liability loans, averaging 2,662 USD, are individual liability, have an average duration of 13.5 months, and repay on a monthly basis. Borrowers cannot simultaneously hold a standard joint-liability loan and a graduation loan. The portion of graduation loan portfolio with 0-30 days late is 4.4%, with 30-60 days late is 1.7%, with 60-90 days late is 0.9%, and over 90 days late is 2.1%.[6]

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.The loan officers who managed the joint-liability loans are entirely non-overlapping with the loan officers who manage the graduation loans. Typically, joint-liability loan officers are trained in social work, while graduation loan officers have backgrounds in business and engineering.

Critically, at the time of our study, joint-liability loan officers received a performance bonus based on the number of borrowers in their own joint-liability 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 joint-liability groups fell below 18, joint-liability loan officers were responsible for replacing lost members by the following loan cycle. Each of these features of their compensation induced penalties on joint-liability 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, joint-liability loan officers were not given any reward for helping qualified borrowers to graduate out of joint-liability credit. We provide a complete description of the compensation scheme employed by our partner lender prior to our intervention in Appendix Section E.

2.1 Experimental Design

In collaboration with our partner lender, we designed two new compensation schemes meant to reduce, and partially reverse the implicit penalty that loan officers face when losing borrowers to graduation. We then conducted an experiment to assess the extent and consequences of strategic communication under the baseline compensation scheme.

[6]We limit our graduation loan sample to borrowers who previously had a joint-liability loan and graduated after our baseline survey; whereas our joint-liability sample comprises all joint-liability borrowers in branches that offer graduation loans.

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]

Compensation Scheme Changes. With our guidance, in March of 2019 our partner lender announced the first change in the compensation scheme for joint-liability loan officers. The new compensation scheme, which we refer to as *Mitigation*, mitigated the penalty that loan officers faced from losing borrowers through graduation. 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.[8] This translated to a reduction in the monetary penalty of losing a graduated borrower of about USD 6 on average, which represents about 0.5% of a loan officer's average compensation. Moreover loan officers now had a full additional loan cycle before they were required to replace lost borrowers for groups that fell below the minimum size of 18. Lastly, to maintain group cohesion as the borrower transitioned out of joint-liability, the borrower who received a graduation loan would be allowed to continue to participate in group meetings and

[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–endorsements–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 endorsements were elicited right before or right after the organizational change. The initial elicitation of endorsements may itself influence the subsequent reporting of endorsements (i.e. a loan officer being asked for a second time for endorsements 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 endorsements among those who have been asked the same number of times, under different compensation schemes.

[8]Recall, the details of this bonus calculation are in Appendix Section E.

group activities for the following year.[9]

In April of 2019 our partner organization announced the second, and final change to loan officer compensation, which we refer to as *Recognition*. In the Recognition scheme, in addition to maintaining the features of Mitigation, loan officers were rewarded (or, recognized) for endorsing borrowers that subsequently went on to receive graduation loans and exhibit good repayment behavior. Rewards were calculated as a function of *points* a loan officer earned—for each borrower that was endorsed and subsequently graduated, loan officers gained three points if the borrower exhibited good repayment behavior and conversely they lost one point for endorsed borrowers who exhibited poor repayment in the graduation loan. 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.

We note that neither of these two compensation schemes is likely to resemble the optimal compensation structure for loan officers. Our goal was not to evaluate the optimal compensation structure, but rather to investigate whether loan officers were strategically withholding information about qualified borrowers under the original compensation scheme. In Section 7 we discuss how our partner lender restructured its organization in response to the results of this study, in a manner that may more closely resemble the theoretically optimal organizational structure.

Surveys, Data, and Timeline. As described in Figure 1, we implemented four rounds of surveys to collect endorsements from joint-liability loan officers about which borrowers would be suitable for graduation. Specifically, loan officers were provided a form with all of their borrowers (organized by joint-liability group) and asked (a) to endorse borrowers who are suitable for graduation and (b) a strength of the endorsement on a scale of 1–5. Loan officers were informed that their endorsements would eventually be used in the graduation process.[10]

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

[9]Loan officers told us that many of the people they were likely to endorse participated in the leadership of the group. They worried that losing those borrowers could harm the group's social cohesion. This was the rationale for allowing graduated borrowers to stay in the group for an extra year, yet anecdotally this was quite rare in practice.

[10]This was indeed the case, though as part of our research protocol we withheld the endorsements from our partner lender until we had enough data to judge the value of endorsements in predicting borrower repayment behavior.

set the explicit expectation that loan officers would be periodically resurveyed to update their endorsements.

The second ($PreMitigation$) occurred five days before the announcement of the Mitigation incentive change in March 2019. We randomly selected half of the joint-liability loan officers – our control group – to be surveyed at the $PreMitigation$ round, during which they were given the opportunity to update the endorsements they provided at baseline. All endorsement surveys were conducted during a weekly branch-wide loan officer meeting. At the $PreMitigation$ survey wave, all loan officers were told they would be asked to update their endorsements, but due to (valid) capacity constraints only half would update their endorsements during that meeting and the other half would be asked to update their endorsements in the meeting the following week.

The third survey ($PostMitigation$) occurred one week after the $PreMitigation$ survey, and two days after the compensation change. All loan officers were surveyed during $PostMitigation$ and given yet another opportunity to update their endorsements.

Our primary comparison of interest is between the endorsements collected by loan officers in the $PreMitigation$ survey round, and the endorsements collected from loan officers in the $PostMitigation$ survey round *who were not also surveyed in the $PreMitigation$ 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 number of endorsements collected from loan officers in the $PreMitigation$ survey round to the number of endorsements collected from the same loan officers in the $PostMitigation$ survey round. We make these comparisons precise in the following section.

Finally, in the week following the announcement of Recognition we implemented one final survey round ($PostRecognition$) to collect endorsements from loan officers. All joint-liability 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 Recognition scheme. Roughly one month elapsed between the $PostMitigation$ and $PostRecognition$ surveys, but we present evidence below that very few of the additional endorsements collected in the $PostRecognition$ survey are due to the elapsed time, and that the great majority of these endorsements are attributable to the compensation shift.

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 joint-liability loans and at the daily level for graduation loans.

Descriptive Statistics and Experimental Balance. Our sample comprises all loan officers and joint-liability borrowers at branches in which our partner lender offers graduation loans from October 2018 to February 2020. This represents 81,220 borrowers and 243 loan officers. Column 1 of Table A1 presents our balance check and sample descriptive statistics. The joint-liability borrowers are on average 46 years old, 20% are male, 39% of them are married and 63% have completed secondary school. The most common business sector is retail, representing 58% of the sample, followed by 29% in manufacturing, and 13% is services. On average, businesses in our sample earn USD 687 per month in profits, and have on average 0.12 non-household workers. The average joint-liability loan size is USD 860, and the average borrower has taken 8 loans from our partner organization. Amongst loan officers who were randomly selected to endorse borrowers before Mitigation versus those who were not, the only statistically significant difference is that borrowers of loan officers surveyed after mitigation 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.

3 The Impact of the Compensation Changes on Communication of Endorsements

In this section we discuss the impact of the two compensation changes on loan officer willingness to endorse borrowers for graduation, and on the characteristics of endorsed borrowers.

The Impact of the Mitigation Scheme

We use two primary regression specifications to evaluate the impact of the Mitigation scheme on the number of endorsements furnished by loan officers. Our preferred specification leverages between-subject variation comparing the number of endorsements we received from loan officers who were surveyed just before the Mitigation scheme was introduced to those who were *only* surveyed just afterwards. This is a comparison of groups A and C in Figure 2. Specifically we regress

$$y_i = \alpha + \beta_1 PostMitigation_i + \gamma X_i + \mu_B + \epsilon_{it} \quad (1)$$

where y_i is the number of endorsements furnished by loan officer i, $PostMitigation_i$ is an indicator for whether loan officer i was only asked for endorsements immediately following the introduction of the Mitigation scheme, μ_B is a branch fixed effect, and X_i is a vector of loan officer controls: total endorsements 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 endorsements received by loan officers under the old incentive scheme and the number received by loan officers under the Mitigation incentive scheme.

Our second specification leverages within-subject variation and compares endorsements 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 Mitigation scheme, we regress

$$y_{it} = \alpha + \beta_2 PostMitigation_{it} + \gamma X_i + \delta_i + \epsilon_{it} \quad (2)$$

where y_{it} is the cumulative number of endorsements furnished by loan officer i in survey round t, δ_i is a loan officer fixed effect, and $PostMitigation_{it}$ is an indicator for whether loan officer i was exposed to the Mitigation scheme in survey round t. Standard errors are clustered at the loan officer level. Here β_2 represents the additional endorsements furnished by loan officers after they were exposed to the Mitigation scheme.

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

$$y_{it} = \alpha + \beta_3 PostMitigation_{it} + \gamma X_i + \mu_B + \epsilon_{it} \quad (3)$$

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 $PreMitigation$, $PostMitigation$, and $PostRecognition$ survey waves.

Table 1 presents our estimates of the impact of the Mitigation scheme on loan officer endorsements. Columns 1 and 2 correspond to estimates of the between-subjects Specification 1 , column 3 corresponds to the within-subjects Specification 2, and columns 4 and 5 correspond to the pooled Specification 3. When there are two columns for a specification, the second includes loan officer controls. Across all specifications, loan officers affected by the Mitigation scheme furnished between 1.1 [SE: 0.28] and 1.6 [SE: 0.53] additional endorsements. This is not only statistically significant but also economically significant. Compared to the $PreMitigation$ round, the loan officers surveyed in the $PostMitigation$ round furnished more than 300 additional endorsements. This is our first piece of experimental evidence that loan officers were strategically withholding endorsements prior to our compensation shift.[11]

Before assessing the impact of the Recognition scheme, we address a possible confound in our analysis of the impact of the Mitigation scheme. Namely, one week elapsed between the $PreMitigation$ survey and the $PostMitigation$ survey. We attribute the difference in the number and quality of endorsements between these survey waves to the introduction of the Mitigation scheme, 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 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 $PreMitigation$ survey without any intervening compensation changes, yet our $PreMitigation$ survey produced almost no new endorsements. 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?[12] We do not think this is a likely confound, as it is not clear what information would be communicated. No loan officer had private information about any aspect of our study. In the $PreMitigation$ survey round all loan officers, both those who were and were not surveyed, knew that an endorsement survey was taking place. And no loan officer knew of the impending compensation changes

[11]We note that the Mitigation compensation change may have induced additional endorsements for reasons other than loan officers' regard for their own compensation. For instance, loan officers may have viewed the compensation shift as a signal that the firm placed higher priority on graduating borrowers and thereby offered more endorsements. Even in this case, that the Mitigation change induced additional endorsements indicates that loan officers had been withholding endorsements prior to the compensation shift. Under this interpretation, one might be concerned that the additional endorsements loan officers furnished after Mitigation were for unqualified borrowers, whose endorsements were only furnished to appease the firm. It is thus important to anticipate that in Section 4 we show that endorsements furnished after Mitigation and Recognition were more valuable to the firm than those furnished at baseline.

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

prior to them taking place. Nevertheless, it is theoretically possible that merely having experienced an additional endorsement survey caused the loan officers surveyed in the $PreMitigation$ wave to communicate with their non-surveyed peers in a manner that caused the latter group to furnish additional endorsements.

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 with one another. For each loan officer i we control for the number of other loan officers that joined our partner lender within six months 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 $PostMitigation$ 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 $PostMitigaiton_{it}$. These results are presented in Table A2.The inclusion of these controls does not materially affect our estimates, and the novel interaction terms are 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 Recognition Scheme

Next we examine the impact of introducing the Recognition scheme. As discussed in Section 2, the Recognition scheme was introduced in April 2019 without random variation. Therefore to evaluate the impact of the Recognition scheme we estimate two regression models

$$y_{it} = \alpha + \beta_1 PostMitigation_{it} + \beta_2 PostRecognition_{it} + \gamma X_i + \delta_i + \epsilon_{it} \tag{4}$$

presented in columns 6 and 7 of Table 1, and

$$y_{it} = \alpha + \beta_1 PostMitigation_{it} + \beta_2 PostRecognition_{it} + \beta_3 PreMitigation_{it} + \gamma X_i + \delta_i + \epsilon_{it} \tag{5}$$

presented in column 8 of Table 1.

In Specification 4 we include data from three of the four survey rounds: the $PreMitigation$ survey wave immediately preceding Mitigation, the $PostMitigation$ survey wave immediately following Mitigation and the $PostRecognition$ survey wave immediately following Recognition. The omitted group is the total number of endorsements given during $PreMitigation$. We exclude data from the $Baseline$ survey wave.

Specification 5 also includes data from the $Baseline$ survey wave, which serves as the omitted group. So we can separately estimate the number of endorsements attributable to the $PreMitigation$ survey wave. In both cases standard errors are clustered at the loan officer level.

Importantly, one month elapsed between the $PostMitigation$ survey and the $PostRecognition$ survey. Therefore, we may not be able to fully attribute all additional endorsements reflected in β_2 to the impact of the Recognition scheme. 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 joint-liability loan program. However, we note that between our baseline in November and our pre-Mitigation survey in February, more than three months elapsed. Assuming that the number of additional endorsements attributable to time is a linear function of time, the coefficient β_3 in Specification 5, corresponding to the additional endorsements we collected in our $PreMitigation$ survey, provides a conservative estimate of the number of additional endorsements from the Recognition 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 Recognition scheme had an impact on loan officer willingness to endorse 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 endorsements as a result of the Mitigation and Recognition scheme 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 endorsements in our $PreMitigation$ survey relative to $Baseline$, indicating that time trends do not account for the additional endorsements we collected $PostRecognition$. Together these comprise our second piece of experimental evidence that loan officers were strategically withholding endorsements of qualified borrowers prior to our 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 endorsements that we collected at baseline, the additional endorsements attributable to the changes in compensation amount to a roughly 11% increase. This in part reflects the efficacy with which we collected endorsements at baseline. Prior to our study, our partner lender received nearly no endorsements from joint-liability loan officers, so the additional endorsements attributable to changes in compensation would amount to an enormous increase, in percentage terms, relative to the endorsements 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* endorsements collected in each survey round. As we will show in Section 4, the borrowers who performed the best in the graduation loan program are those who were endorsed after Mitigation and Recognition rather than those endorsed at baseline. This suggests that it was the *most qualified* borrowers whose endorsements loan officers were strategically withholding prior to the compensation shift.

4 The Predictive Power of Endorsements

Our next line of inquiry regards the value of endorsements furnished across the various survey rounds in predicting the repayment behavior and business growth of borrowers. In this section we demonstrate that loan officer endorsements are valuable in predicting the repayment behavior both in the joint-liability portfolio and in the graduation portfolio. Endorsements also predict business growth from graduation loans. In each of these cases, endorsements remain valuable even after controlling for observable characteristics. Hence loan officers have valuable soft information not easily inferable from borrower characteristics.

Importantly we find evidence that borrowers endorsed after Mitigation and after Recognition exhibit better repayment behavior and more business growth than borrowers endorsed at baseline. This is our final, and perhaps most striking finding regarding loan officer strategic communication. 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 endorsed after Mitigation and Recognition have better performance in *both* portfolios represents an important misalignment between the interests of loan officers and those of our partner lender. 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 in this section indicate that this misalignment of interests is important in practice.

Endorsements 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 joint-liability loan officer endorsements with our partner lender.[13] Therefore, the graduation procedure was not informed by the endorsements we collected in our survey. So this section can be understood as evaluating the predictive value of endorsements 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,

$$y_{it} = \alpha + \beta_S EndorsedInRoundS_i + \gamma X_i + \mu_B + \phi_t + \epsilon_{it} \tag{6}$$

where y_{it} is a measure of borrower i's repayment behavior in month t, and $EndorsedInRoundS_i$ is an indicator for whether borrower i was endorsed in survey round S ($Baseline$, $PostMitigation$, and $PostRecognition$).[14] We use double post lasso to select control variables X_i from the set of borrower characteristics presented in Table A1. Due to our sample size, we include branch μ_B and month 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 endorsed in round S and subsequently graduated, and borrowers who were never endorsed in any round but who graduated after survey round S, so that they were eligible to be endorsed in survey round S. So for the baseline endorsement survey, the sample includes any borrower who was either endorsed at baseline or never endorsed, and who received a graduation loan sometime after November 2018. For endorsements collected in the $PostMitigation$ survey it includes any borrower who was either endorsed in the $PostMitigation$ round or never endorsed, and who received a loan sometime af-

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

[14] For this part of the analysis, we combine endorsements given in the first survey round (baseline - November 2018) and the second survey round ($PreMitigation$- last week of February 2019) since the loan officer incentives were the same for both those rounds. As we showed in Section 3, the passage of time has no significant effect on the number of endorsements that we received.

ter March 2019. And in the $PostRecognition$ survey it includes any borrower who was either endorsed in the $PostRecognition$ round or never endorsed, and who received a loan after April 2019. By holding fixed the comparison group to be those who were never endorsed in any round, this approach allows for evaluation of the predictive power of endorsements 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 2 contains data from the relevant survey waves to October, 2022, at which point all graduation loans in our study had either been fully repaid or written off. In Appendix Table A3 we include analogous estimates based on data from the relevant survey wave to February, 2020 just after Chile's shutdown for COVID-19. At this point our partner lender implemented a 3 month repayment freeze, and subsequently suffered additional defaults, so we analyze this period separately. 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" during her loan cycle (columns 5 and 6), and the total value in default (columns 7 and 8).[15] 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 controls for observable characteristics while odd columns do not.

Beginning with the the long-term repayment results in Table 2, we see that with few exceptions, borrowers who were endorsed after the compensation changes exhibit better repayment behavior than those who were not endorsed on every dimension. Estimates are highly stable with respect to the inclusion of controls, suggesting that loan officers have valuable information about borrower repayment capacity that is not well encoded by observable characteristics.[16] In contrast, none of the estimates for endorsements furnished at baseline suggest that endorsed borrowers exhibited better repayment.

The magnitudes of the point estimates for endorsements furnished after the compensa-

[15]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.

[16]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 endorsements.

tion change are economically meaningful. For instance, compared to graduated borrowers who were never endorsed, graduated borrowers endorsed after Mitigation or Recognition are 19.2 [SE: 8.2] percentage points less likely to default in a binary sense, and default on USD 343.1 [SE: 143.1] less, on average. The estimates for endorsements furnished at baseline are not economically meaningful, and are never statistically significant. The fact that borrowers endorsed after Mitigation and after Recognition have better repayment profiles than those endorsed at baseline, and often statistically significantly so, suggests that loan officers were withholding endorsements of their best borrowers prior to the compensation shifts.

The estimates in appendix Table A3, which restricts the repayment window from the relevant endorsement survey to February 2020, tell a very similar story. Baseline endorsements are not predictive of default, while endorsements furnished after Mitigation and Recognition are predictive, almost always statistically significantly so. The point estimates are smaller, as there is less default in the portfolio overall, though they are still meaningful. For instance, borrowers endorsed after Mitigation or Recognition are 2.4 [SE: 0.7] percentage points less likely to default in a binary sense, and default on USD 50.0 [SE: 16.5] less, on average.

Finally, in Table A4 we re-estimate Specification 6, but replace $EndorsedInRoundS_i$ with a continuous measure of endorsement strength (recall that our loan officer survey elicited a 1-5 measure of endorsement strength). Results are qualitatively similar and suggest that the intensive margin of endorsement strength adds little predictive power over the extensive measure used in our primary analysis.

Endorsements Predict Joint-Liability Loan Performance

In this section we document the predictive power of loan officer endorsements on borrowers in joint-liability loans. Relative to graduation loans, this has the advantage that we observe the outcome for all borrowers independent of whether they were eventually selected to graduate. However the regressions on joint-liability repayment behavior also have two drawbacks. First, we asked loan officers to endorse borrowers on the basis of their suitability for graduation loans; loan officers were not asked to predict repayment behavior in joint-liability loans per se. However, this should serve to reduce the predictive power of endorsements relative to if loan officers had been asked to endorse borrowers on the basis of their suitability for joint-liability loans. As we will demonstrate, endorsements are nevertheless quite predictive of joint-liability repayment behavior. The second drawback 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. Once again this should serve to reduce the predictive power of individual endorsements and we show below that they are nevertheless strong predictors of repayment.

We estimate regression models analogous to those in the section above. Namely, for each survey round S we estimate

$$y_{it} = \alpha + \beta_S EndorsedInRoundS + \gamma X_i + \delta_L + \phi_t + \epsilon_{it} \tag{7}$$

on the sample of borrowers who have joint-liability loans in months after their eligibility to be endorsed in a given survey round. In each regression, we restrict the sample to borrowers who were never endorsed and borrowers who were endorsed in round S. Standard errors are clustered at the borrower level. In contrast to Specification 6, our sample of joint-liability borrowers is large enough that we can include loan officer fixed effects δ_L, rather than branch fixed effects μ_B.

Results are presented in Table 3, for the same outcomes as in Table 2. In contrast to the case of graduation loans, all joint liability loans in our sample concluded prior to February 2020, so we do not include separate analyses of short- and long-run results. In accordance with our partner lender's definitions, default for joint-liability loans is defined as whether a borrower is 90 days late and reported to the credit bureau.

The patterns are qualitatively similar to the graduation loans analysis. Across all survey waves, endorsed borrowers exhibit less default than non-endorsed borrowers. For joint-liability loans, borrowers endorsed at baseline have statistically significantly lower default than those never endorsed, across all measures except amount defaulted (columns 7 and 8). Estimates are almost all statistically significant across outcomes for borrowers endorsed after Mitigation and after Recognition. With very few exceptions, borrowers endorsed after Mitigation and after Recognition have lower measures of default than those endorsed in baseline, and the differences are statistically significant for the outcome variables 90 days late and amount defaulted for borrowers endorsed after Mitigation, and for the outcome variables default and amount defaulted for borrowers endorsed after Recognition. This further suggests that loan officers withheld endorsements of their most qualified borrowers prior to the compensation shifts.

While default is a smaller problem in our partner lender's joint-liability loan portfolio than in their graduation portfolio, the estimates on the value of endorsements in predicting default are still economically meaningful. For instance, relative to borrowers who were never endorsed, borrowers endorsed after Recognition are 0.7 [SE: 0.3] percentage point less likely to be 15 days late off of a baseline of 1.3 percentage points, and on average default on USD 9.1 [SE: 4.5] less, off of a baseline of USD 13.6. Further, as was the case with graduation loans, the estimates are quite stable with respect to the inclusion of controls, suggesting that loan officers form their endorsements on the basis of information that is not easily observed or encoded.

As in the analysis of graduation loans, in Table A5 we re-estimate Specification 7, but replace $EndorsedInRoundS_i$ with a continuous measure of endorsement strength. Results are qualitatively similar and suggest that the intensive margin of endorsement strength adds little predictive power over the extensive measure used in our primary analysis.

The fact that borrowers endorsed after Mitigation and Recognition exhibited better repayment in their joint-liability loans than those endorsed at baseline (and those never endorsed) is an important factor in explaining why these endorsements were withheld at baseline. Borrowers with good joint-liability repayment are exactly the ones loan officers would like to keep within their portfolios. Importantly, we found in the previous section that borrowers endorsed after Mitigation and Recognition also exhibited better repayment in the graduation portfolio, and hence these are the borrowers that our partner lender would most like to be endorsed. 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 their joint-liability microloans.

One potential caveat to the above conclusion is the possibility that in graduating endorsed 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.

Loan Officer Endorsements Predict Borrower Business Growth Following Graduation Loans

Next, we establish that loan officer endorsements are predictive of how much borrowers' profits grow following receipt of a graduation loan. As in the case of predicting repayment, we show that endorsements furnished after Mitigation and Recognition 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 endorsements 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 in 2018, prior to any borrower in our sample graduating, and again each time they renew their loans from 2020 to 2022. On the sample of borrowers who eventually receive graduation loans, we estimate

$$\begin{aligned} y_{it} = \alpha + \beta_1 EndorsedBaseline_i + \beta_2 EndorsedAfter_i + \gamma Graduation_{it} + \\ \delta_1 Graduation_{it} * EndorsedBaseline_i + \delta_2 Graduation_{it} * EndorsedAfter_i + \epsilon_{it} \end{aligned} \tag{8}$$

where y_{it} is borrower i's profit in period t, $EndorsedBaseline_i$ is an indicator variable taking a value of 1 if borrower i was endorsed at baseline and 0 otherwise, $EndorsedAfter_i$ is an indicator variable taking a value of 1 if borrower i was endorsed after either compensation change and 0 otherwise, 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 also include borrower controls, borrower fixed effects, and calendar-time fixed effects in alternative specifications. Standard errors are clustered at the borrower level. Due to sample size limitations, we do not separately investigate the growth in profits for borrowers endorsed after Mitigation and after Recognition.

The estimates are presented in Table 4. Three features of the results are of note. First, the estimate of γ indicates that on average, borrowers who were not endorsed in any round experienced significant growth in their profits after receiving a graduation loan. For instance, the estimates in column 3 indicate that their monthly profits grew by USD 880 [SE: 112]. Second, although borrowers endorsed in the baseline survey wave had significantly higher profits at baseline, the estimates of δ_1 indicate they did not experience any additional profits growth upon receiving a graduation loan relative to borrowers who were never endorsed. Finally, the estimates of δ_2 indicate that borrowers endorsed after the compensation change experienced nearly twice as much profit growth upon receiving a graduation loan, relative to borrowers endorsed at baseline and those never endorsed. For instance, the estimates in column 3 indicate that borrowers endorsed after the compensation changes experienced an additional USD 882 [SE: 388] in profit growth. Throughout all specifications, δ_2 is statistically significantly larger than δ_1 at at least the 10% level.

That endorsements 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.

5 Strategic Determinants of Endorsements

In this section we examine how the characteristics of endorsed borrowers varied over our successive interventions to illuminate the strategic decision making of loan officers.

5.1 The Cost of Losing a Borrower

Our first exercise is to examine the causal relationship between the cost of losing a borrower – in terms of forgone compensation as of our baseline in November 2018 – and the likelihood a loan officer endorses her for graduation. Due to the complexity of the exercise, we defer a complete description and analysis to Appendix Section C. Here we provide a brief overview.

Establishing the relationship between the cost of losing a borrower and the likelihood a loan officer endorses her entails two challenges. The first challenge is to determine the cost to a loan officer of losing her borrower. We compute two estimates of this cost. The first, which we term *DirectCost*, is to calculate the difference between what a loan officer would earn with a given borrower in her portfolio, and what she would earn without that borrower in her portfolio, holding the rest of her portfolio constant. The drawback of this approach is that loan officers are compensated via a piecewise linear function that has several discontinuous jumps when their portfolio crosses certain thresholds. Therefore the *DirectCost* of losing a borrower is zero in most cases and very large in a few cases, but this ignores the real cost that loan officers face when losing a borrower pushes them nearer to a threshold without actually inducing them to cross it. We therefore complement our measure of *DirectCost* with an alternative measure of the cost of losing a borrower based on a computationally tractable approximation of the Shapley Value – a notion from cooperative game theory that determines the value any member adds to an arbitrary coalition. The *ShapleyCost* smooths out the discontinuities in *DirectCost* by accounting for how close to a compensation threshold a loan officer would be pushed if she were to lose a given borrower.

The second challenge relates to identifying the causal effect of the financial penalty of losing a borrower on the likelihood of endorsement. Borrowers who are costlier to lose are the ones with larger loans and with better repayment histories, and as a result they may also be better suited for graduation loans. Therefore, a naive regression of whether a borrower is endorsed on the cost of losing her may not identify the causal impact of the financial penalty on the likelihood of endorsement. We circumvent this problem by instrumenting the cost of losing a borrower with features of each loan officer's portfolio of borrowers. Namely, as referenced above, loan officers face discontinuous jumps in their compensation at certain thresholds for number of borrowers in their portfolio and repayment rates, and loan officers who are nearer to these thresholds have a higher cost of losing their borrowers. We use a loan officer's distances to each of these thresholds as instruments for the cost of losing a borrower. So long as these distances are uncorrelated with a loan officer's propensity to endorse borrowers for graduation, except insofar as they are correlated with the cost of losing a borrower, these are valid instruments.

Our analysis yields two results. First, at baseline, the cost of losing a borrower is an important deterrent to endorsements. We estimate that a one standard deviation increase in either *DirectCost* or *ShapleyCost* corresponds to about a 1 percentage point reduction in the likelihood a borrower is endorsed, or about a 15% reduction of the baseline likelihood of endorsements. The second result is that this relationship attenuates significantly after the compensation changes. This suggests that loan officers internalized that our compensation shifts disproportionately reduce the cost of endorsing borrowers that were more important to their compensation in the baseline scheme.

5.2 Other Borrower Characteristics

Turning away from the cost of losing a borrower, we next examine a range of other observable characteristics of borrowers who were endorsed in each survey round; these are presented in Table 5. Column 1 presents the average characteristics across all borrowers, column 2 present the average characteristics for borrowers endorsed at baseline, and columns 3 and 4 present the difference in average characteristics between borrowers endorsed at baseline and borrowers endorsed after Mitigation, and after Recognition respectively. Relative to the whole population of borrowers, those endorsed at baseline run larger and more profitable businesses, earning approximately an additional USD 330 a month. They have been with our partner lender for approximately 2.7 additional loan cycles, their amount borrowed is about USD 347 larger, and they spend fewer days in default.

There are few differences in observable characteristics between borrowers endorsed at baseline and those endorsed after our compensation shifts. Relative to borrowers endorsed at baseline, borrowers endorsed after Mitigation are about two years younger. In terms of borrowing characteristics, they have been with the organization for 0.9 fewer loan cycles relative to a baseline of 10.7, and have slightly smaller loans – on average USD 53 less compared to a baseline of USD 1,207. The only statistically significant difference between the observable characteristics of borrowers endorsed after Recognition and those endorsed at baseline is that those endorsed after Recognition are less likely to be in agriculture. Few, if any of these differences are economically meaningful in their magnitudes.

Comparing borrowers endorsed across various survey rounds based on the size of their joint-liability group reveals a new dimension on which loan officers were strategically withholding endorsements prior to the compensation shift. Recall that when joint-liability groups fall below 18 borrowers, joint-liability loan officers face significant pressure to replace lost borrowers. Therefore loan officers may have been particularly wary to endorse borrowers from groups at or near 18 borrowers. Our Mitigation compensation scheme reduced the pressure to immediately replace lost borrowers, and our Recognition scheme increased the reward from identifying reliable borrowers regardless of their group size. Therefore both compensation schemes may have had an especially large effect in inducing loan officers to disclose their endorsements of borrowers from smaller groups. Figure 3 suggests that this was the case.

Figure 3 on the left depicts the distribution of group sizes from borrowers endorsed at baseline, and overlays the distribution of group sizes of borrowers endorsed after Mitigation. Figure 3 on the right does the same for borrowers endorsed at baseline and those endorsed after Recognition. While there is no apparent difference in the distributions for baseline and Mitigation, there is more mass in the left tail of the Recognition distribution than there is in the left tail of the baseline distribution. Specifically, a Kolmogorov-Smirnov test rejects equality of the baseline and Recognition endorsement distributions, and a t-test rejects that the two distributions have the same amount of mass to the left of both 18 and 20 borrowers at the 1% level. Therefore, borrowers from small groups—those less than 20 borrowers—had higher representation in the Recognition endorsements than in the baseline endorsements. This suggests that indeed loan officers were more likely to strategically withhold the endorsements of borrowers from smaller groups.

6 Broader Applicability of Our Results

How far do the results of this study extend beyond our partner lender? To address this question we draw on two data sources to assess the prevalence of the managerial practices that give rise to a misalignment of interests between loan officers and their borrowers.

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." 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 40 microfinance institutions in South America and India. These institutions were reached through personal contacts of our partner lender, and the Harvard Business School research centers in India and South America, and are listed in Figure 4. Our survey was distributed to managers within these institutions who reported to know about how loan officers were compensated, and the questions included whether the institution has a graduation program, whether distinct loan officers manage the microcredit loans and graduation loans, whether loan officers receive monetary compensation based on the size and repayment rate of their portfolio, and whether they provided any special bonus for loan officers whose borrowers graduated to larger loans.

Of these 40 institutions, 65% report having an internal graduation program.[17] And of those MFIs with an internal graduation program, between 31% and 54% 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.[18] 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.[19] 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 up to half of all microfinance institutions with graduation programs. In turn these results suggest that a misalignment of interests between loan officers and their borrowers may be an important contributor to the disappointing impact that microcredit has had on livelihoods.

More broadly, our results may generalize to other organizational settings in which social efficiency dictates that a “principal" must relinquish control of their “agent." Examples of such arrangements include managers who lose their subordinates to promotion and professors who lose their graduate students and postdocs to graduation. In each of these settings the supervising party derives value from the continued interaction with their subordinate, and they have the discretion to help or hinder their subordinate’s career advancement. Viewed in this light our results present a proof of concept that these theoretical misalignments of interest manifest in important ways in practice.

[17]Specifically, 65% of responding managers reported that their MFI "offers a loan product that is larger than your standard microloan."

[18]The uncertainty in this range is due to the fact that several managers reported they did not know whether loan officers were compensated based on the size and repayment of their portfolio, or did not know whether loan officers were given a bonus for graduated borrowers.

[19]Interestingly, of those MFIs whose practices do not induce a misalignment of interests between loan officers and borrowers, 83% have a single loan officer manage both loan products, 25% do not provide monetary incentives for the size and repayment rate of loan officers’ portfolios, and 17% offer a bonus to loan officers when a borrower graduates out of their portfolio.

7 Discussion

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.

In partnership with a large Chilean microfinance institution that offers both joint-liability and larger graduation loans, we conducted an experiment in which we reduced the penalty that joint-liabiltiy loan officers suffered from borrower graduation. We find that loan officers with modified compensation schemes furnished several hundred more endorsements for borrower graduation, representing an increase in endorsements of about 11% relative to the number we collected at baseline and a far larger increase relative to the number of endorsements our partner lender collected prior to our study. Further, relative to those endorsed at baseline, graduated borrowers endorsed after the compensation changes exhibited significantly better repayment of their graduation loans and enjoyed significantly more profits growth following graduation. This indicates that not only were loan officers strategically withholding endorsements from qualified borrowers prior to the compensation shift, but further that they were withholding endorsements from *their most* qualified borrowers. Our experimental design may also prove useful to researchers desiring to conduct experiments within large organizations, where managers may be reluctant to treat employees differently from one another.

Utilizing the MIX Market dataset as well as a novel survey of 40 microfinance institutions around the world, we document the widespread usage of incentive schemes that penalize loan officers for borrower graduation. Thus our results may shed new light on the limited impact that microcredit has had 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, 2020). 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 joint-liability 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.

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A Main Tables and Figures

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

	Total Cumulative Endorsements							
	Between Officers		Within Officers	All Officers		All Officers		All Officers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_1: Post Mitigation	1.111***	1.086***	1.626***	1.334***	1.322***	1.309***	1.296***	1.614***
	(0.278)	(0.279)	(0.526)	(0.268)	(0.268)	(0.272)	(0.273)	(0.295)
β_2: Post Recognition						2.167***	2.145***	2.432***
						(0.335)	(0.337)	(0.376)
β_3: Pre Mitigation								0.119
								(0.236)
P-value for F Test: $\beta_1 = \beta_2$						0.000	0.000	0.000
P-value for F Test: $\beta_1 = \beta_3$								0.000
Mean: Endorsements pre Mitigation	0.187	0.187	0.187	0.187	0.187	0.187	0.187	
	[0.862]	[0.862]	[0.862]	[0.862]	[0.862]	[0.862]	[0.862]	
Mean: Endorsements at Baseline	20.437	20.437	21.896	20.924	20.924	20.914	20.914	20.776
	[27.007]	[27.007]	[31.571]	[28.601]	[28.601]	[28.201]	[28.201]	[27.844]
Branch FE	X	X		X	X	X	X	
Loan Officer FE			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

Notes: **Specification**: Columns (1)-(2) implement Specification 1, Column (3) implements Specification 2, Columns (4)-(5) implement Specification 3, Columns (6)-(7) implement Specification 4, and Column (8) implements Specification 5. Standard errors are in parentheses. Standard errors are clustered at the loan officer level. Standard deviations are in brackets. Columns (1)-(5) only include the February and March survey waves, and Columns (6)-(7) include the pre-mitigation round in February, the post mitigation round in March, and the post recognition round in April. Pre-mitigation is the omitted group in all regressions in Columns (1) - (7). Column (8) includes the November Baseline, February, March, and April survey waves. The omitted group is the baseline endorsements wave. Loan officer controls include the total number of endorsements made in November Baseline, size of total loan portfolio in November 2018, and number of borrowers in the loan officer's portfolio in November 2018. Columns (1),(2),(4),(5),(6),(7) have branch fixed effect while columns (3) and (8) have loan officer fixed effects. Columns (2), (5) and (7) have officer controls. **Outcome variable**: Columns (1)-(8) report results on the total cumulative number of endorsements made by a loan officer by each survey round.

Table 2: Do endorsements predict repayments for Graduation loans?

	Late ≥ 15 days		Late ≥ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Endorsements								
$\beta_{Baseline}$: Endorsed at Baseline	0.007	0.008	-0.004	-0.003	0.017	0.022	23.553	23.553
	(0.020)	(0.020)	(0.012)	(0.012)	(0.042)	(0.041)	(86.480)	(86.360)
Mean: Not Endorsed	0.183	0.183	0.098	0.098	0.374	0.374	559.170	559.170
	[0.387]	[0.387]	[0.297]	[0.297]	[0.484]	[0.484]	[1019.316]	[1019.316]
Lasso Controls		X		X		X		X
Number of Borrowers	719	719	719	719	719	719	719	719
Observations	44458	44458	44458	44458	719	719	719	719
Panel B: Mitigation Endorsements								
$\beta_{Mitigation}$: Endorsed at Mitigation	-0.093*	-0.091*	-0.050	-0.047	-0.358***	-0.361***	-590.429***	-594.187***
	(0.052)	(0.055)	(0.039)	(0.041)	(0.023)	(0.023)	(52.097)	(53.066)
Mean: Not Endorsed	0.191	0.191	0.101	0.101	0.358	0.358	590.429	590.429
	[0.393]	[0.393]	[0.302]	[0.302]	[0.480]	[0.480]	[1106.442]	[1106.442]
Lasso Controls		X		X		X		X
Number of Borrowers	466	466	466	466	466	466	466	466
Observations	29900	29900	29900	29900	466	466	466	466
Panel C: Recognition Endorsements								
$\beta_{Recognition}$: Endorsed at Recognition	-0.003	-0.003	-0.017	-0.017	0.038	0.033	-29.818	-29.818
	(0.067)	(0.067)	(0.040)	(0.040)	(0.157)	(0.157)	(291.780)	(291.059)
Mean: Not Endorsed	0.198	0.198	0.105	0.105	0.362	0.362	623.459	623.459
	[0.398]	[0.398]	[0.307]	[0.307]	[0.481]	[0.481]	[1143.548]	[1143.548]
Lasso Controls		X		X		X		X
Number of Borrowers	405	405	405	405	405	405	405	405
Observations	25807	25807	25807	25807	405	405	405	405
Panel D: Mitigation or Recognition Endorsements								
β_{MoR}: Endorsed at Mitigation or Recognition	-0.057	-0.053	-0.037	-0.034	-0.192**	-0.189**	-343.078**	-340.154**
	(0.043)	(0.045)	(0.030)	(0.031)	(0.080)	(0.082)	(143.149)	(148.029)
Mean: Not Endorsed	0.191	0.191	0.101	0.101	0.358	0.358	590.429	590.429
	[0.393]	[0.393]	[0.302]	[0.302]	[0.480]	[0.480]	[1106.442]	[1106.442]
Lasso Controls		X		X		X		X
Number of Borrowers	476	476	476	476	476	476	476	476
Observations	30428	30428	30428	30428	476	476	476	476
P-Value for F test:								
$\beta_{Baseline} = \beta_{Mitigation}$	0.066	0.063	0.254	0.249	0.000	0.000	0.000	0.000
$\beta_{Baseline} = \beta_{Recognition}$	0.891	0.881	0.745	0.735	0.895	0.895	0.858	0.856
$\beta_{Mitigation} = \beta_{Recognition}$	0.279	0.279	0.552	0.552	0.011	0.011	0.050	0.050
$\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.167	0.161	0.292	0.285	0.014	0.014	0.019	0.018

Notes: **Specification**: This table implements Specification 6. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. 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, endorsed borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers endorsed at that given round and those never endorsed. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Only borrowers endorsed at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never endorsed at any round. The sample in every panel is limited to the first completed graduation loan that is disbursed after the respective survey. Data utilized comes from reports between November 2018 and October 2022. Odd columns do not include any control variables. Even columns include double-post lasso controls for average days late before Baseline, and demographic and business characteristics from Table A1. Tests of equality of Baseline and Post Mitigation, Baseline and Post Recognition, Post Mitigation and Post Recognition, and Baseline and Post Mitigation or Post Recognition 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 endorsement wave, up to October 2022. 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 endorsement wave, up to October 2022. Columns (5)-(6) report results on an indicator variable for ever defaulted on a Graduation loan in the months after each endorsement wave, up to October 2022. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each endorsement wave, up to October 2022.

Table 3: Do endorsements predict repayments for Joint-Liability loans?

	Late $\geq$ 15 days		Late $\geq$ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Endorsements								
$\beta_{Baseline}$: Endorsed at Baseline	-0.007***	-0.002***	-0.001***	-0.000	-0.008***	-0.005**	-0.331	-1.910
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(1.607)	(1.674)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.025	0.025	11.741	11.741
	[0.115]	[0.115]	[0.044]	[0.044]	[0.156]	[0.156]	[99.888]	[99.888]
Lasso Controls		X		X		X		X
Number of Borrowers	75299	75299	75299	75299	75299	75299	75299	75299
Observations	3342287	3342287	3342287	3342287	75299	75299	75299	75299
Panel B: Mitigation Endorsements								
$\beta_{Mitigation}$: Endorsed at Mitigation	-0.008***	-0.007***	-0.001***	-0.001***	-0.015**	-0.013**	-8.648***	-9.992***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.006)	(0.006)	(2.651)	(2.705)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.027	0.027	12.869	12.869
	[0.111]	[0.111]	[0.043]	[0.043]	[0.163]	[0.163]	[104.504]	[104.504]
Lasso Controls		X		X		X		X
Number of Borrowers	64797	64797	64797	64797	64797	64797	64797	64797
Observations	2520606	2520606	2520606	2520606	64797	64797	64797	64797
Panel C: Recognition Endorsements								
$\beta_{Recognition}$: Endorsed at Recognition	-0.007**	-0.006**	-0.001	-0.001	-0.023***	-0.021***	-9.078**	-10.112**
	(0.003)	(0.003)	(0.001)	(0.001)	(0.006)	(0.007)	(4.545)	(4.608)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.029	0.029	13.616	13.616
	[0.113]	[0.113]	[0.045]	[0.045]	[0.168]	[0.168]	[107.458]	[107.458]
Lasso Controls		X		X		X		X
Number of Borrowers	61081	61081	61081	61081	61081	61081	61081	61081
Observations	2119964	2119964	2119964	2119964	61081	61081	61081	61081
Panel D: Mitigation or Recognition Endorsements								
β_{MoR}: Endorsed at Mitigation or Recognition	-0.008***	-0.007***	-0.001***	-0.001***	-0.017***	-0.015***	-8.579***	-9.875***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.005)	(0.005)	(2.322)	(2.365)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.027	0.027	12.869	12.869
	[0.111]	[0.111]	[0.043]	[0.043]	[0.163]	[0.163]	[104.504]	[104.504]
Lasso Controls		X		X		X		X
Number of Borrowers	64961	64961	64961	64961	64961	64961	64961	64961
Observations	2527065	2527065	2527065	2527065	64961	64961	64961	64961
P-Value for F test:								
$\beta_{Baseline} = \beta_{Mitigation}$	0.586	0.003	0.124	0.000	0.280	0.114	0.006	0.020
$\beta_{Baseline} = \beta_{Recognition}$	0.954	0.115	0.873	0.478	0.025	0.006	0.068	0.114
$\beta_{Mitigation} = \beta_{Recognition}$	0.714	0.714	0.443	0.443	0.382	0.382	0.934	0.934
$\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.579	0.001	0.288	0.002	0.068	0.014	0.003	0.011

Notes: **Specification**: This table implements Specification 7. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. 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, endorsed borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers endorsed at that given round and those never endorsed. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Only borrowers endorsed at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never endorsed at any round. The sample for each panel is limited to every completed joint liability loan that was disbursed after the respective survey round. Data utilized comes from reports between November 2018 and February 2020. Odd columns do not include any control variables. Even columns include double-post lasso controls for average days late before Baseline, and demographic and business characteristics from Table A1. Tests of equality of Baseline and Post Mitigation, Baseline and Post Recognition, Post Mitigation and Post Recognition, and Baseline and Post Mitigation or Post Recognition 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 endorsement wave, up to February 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 endorsement wave, up to February 2020. Columns (5)-(6) report results on an indicator variable for ever defaulted on a Graduation loan in the months after each endorsement wave, up to February 2020. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each endorsement wave, up to February 2020.

Table 4: Do endorsments predict profits growth for borrowers who graduated?

	Profits		
	(1)	(2)	(3)
β_1: Endorsed at Baseline	402.795*	405.696*	406.084*
	(237.442)	(235.808)	(235.171)
β_2: Endorsed at Mitigation or Recognition	108.845	-158.762	108.832
	(465.144)	(261.984)	(452.899)
γ: Had Graduated	837.172***	837.379***	845.406***
	(115.546)	(114.750)	(115.323)
δ_1: Endorsed at Baseline $\times$ Had Graduated	-12.688	-12.896	-25.340
	(285.084)	(283.170)	(286.071)
δ_2: Endorsed at Mitigation or Recognition $\times$ Had Grad	941.055**	799.712*	936.877**
	(389.881)	(436.144)	(387.477)
Mean: Not Endorsed	1483.462	1483.462	1483.462
	[1214.947]	[1214.947]	[1214.947]
Lasso Controls		X	
Borrower Fixed Effects			X
Number of Borrowers	165	165	165
Observations	686	686	686
P-value for F Test: $\delta_1 = \delta_2$	0.037	0.100	0.035

Notes: This table implements Specification 8. Sample is limited to the graduate borrowers that are active after the recommendation survey rounds and have filled the application form for a new loan after 2020. The outcome variable is the business profits. Models are estimated using OLS. Standard errors are clustered at the borrower level. Profits are top-coded at the 99.95th percentile. The omitted group are the graduate borrowers who were not endorsed. Column 1 does not include any control variables. Column 2 includes double-post lasso controls for average days late before Baseline, and demographic and business characteristics from Table A1. Column 3 includes borrower fixed effects. Tests of equality of the coefficients are based on the SURS framework.

Table 5: Borrower Characteristics by Endorsement Round

	All Borrowers	Endorsed at Baseline	Endorsed at Mitigation	Endorsed at Recognition
	Mean	Mean	Difference from Baseline	Difference from Baseline
	(1)	(2)	(3)	(4)
Age	45.920	47.769	-1.877***	0.036
	[13.126]	[11.549]	(0.620)	(0.912)
Gender: Male	0.195	0.276	0.022	-0.038
	[0.396]	[0.447]	(0.026)	(0.034)
Married	0.396	0.463	-0.040	-0.030
	[0.489]	[0.499]	(0.028)	(0.039)
HH Size	3.671	3.694	0.039	0.068
	[1.589]	[1.568]	(0.094)	(0.139)
Education: Secondary and Above	0.628	0.670	-0.040	0.007
	[0.483]	[0.470]	(0.027)	(0.037)
No. of Non-HH Workers	0.122	0.277	-0.101**	-0.014
	[0.987]	[1.539]	(0.043)	(0.076)
Sector: Manufacturing	0.289	0.270	-0.028	0.030
	[0.454]	[0.444]	(0.024)	(0.037)
Sector: Retail	0.582	0.587	0.025	-0.018
	[0.493]	[0.492]	(0.028)	(0.040)
Sector: Services	0.124	0.140	0.003	-0.009
	[0.330]	[0.347]	(0.020)	(0.027)
Sector: Agriculture	0.004	0.003	0.000	-0.003***
	[0.065]	[0.055]	(0.003)	(0.001)
Monthly Business Revenues (USD)	1043.600	1531.389	-135.387**	-145.567
	[763.594]	[921.851]	(63.699)	(95.386)
Monthly Business Profits (USD)	694.933	1022.920	-65.877*	-76.013
	[522.079]	[616.232]	(39.426)	(59.738)
Borrower Cycle	8.234	10.859	-1.030**	-0.401
	[7.249]	[7.749]	(0.433)	(0.671)
Amount Borrowed (USD)	875.823	1214.219	-60.574**	-48.605
	[527.100]	[529.392]	(30.316)	(41.600)
Amount Late (USD)	1.938	0.544	0.976	0.005
	[19.665]	[7.669]	(0.651)	(0.558)
Days Late	0.243	0.027	0.036	0.007
	[2.692]	[0.461]	(0.040)	(0.035)
Observations	76,196	4,689	5,022	4,853

Notes: Column (1) reports average borrower characteristics as of the 1st of November 2018, for *all* borrowers who had an active loan at our partner lender and were evaluated during that month. Column (2) reports average characteristics of borrowers who were endorsed at Baseline or endorsed at Pre-Mitigation in February 2019, just before the Mitigation scheme was announced, since at Baseline and at Pre-Mitigation the compensation scheme is the same. Columns (1) and (2) report standard deviations in brackets. Column (3) reports the mean difference in characteristics of borrowers who were endorsed at Mitigation, from borrowers who were endorsed at Baseline (column (2)). Column (4) reports the mean difference in characteristics of borrowers who were endorsed at Recognition, from borrowers who were endorsed at Baseline ((2)). Columns (3) and (4) report robust standard errors in parentheses.

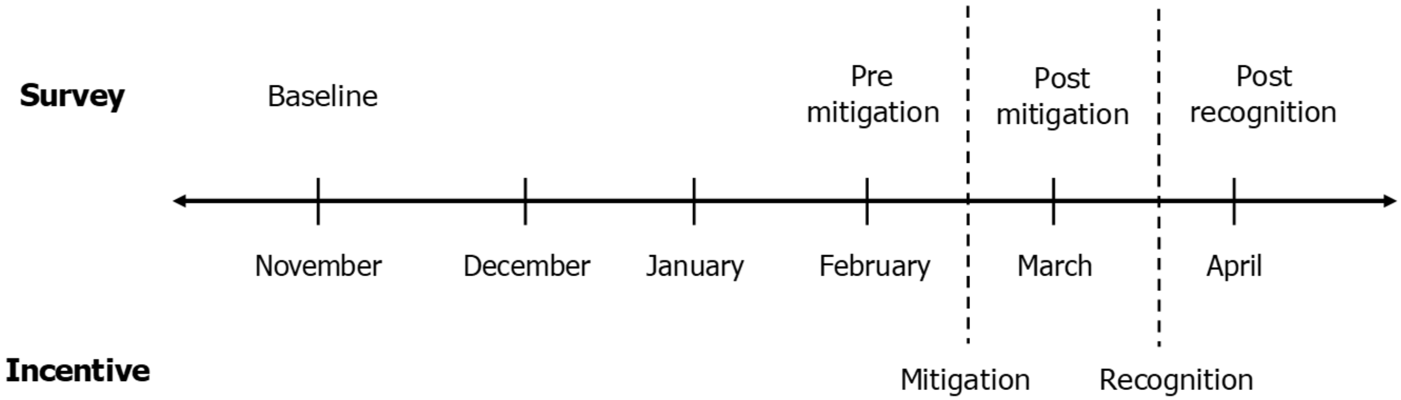

Figure 1: Intervention and Survey Timeline

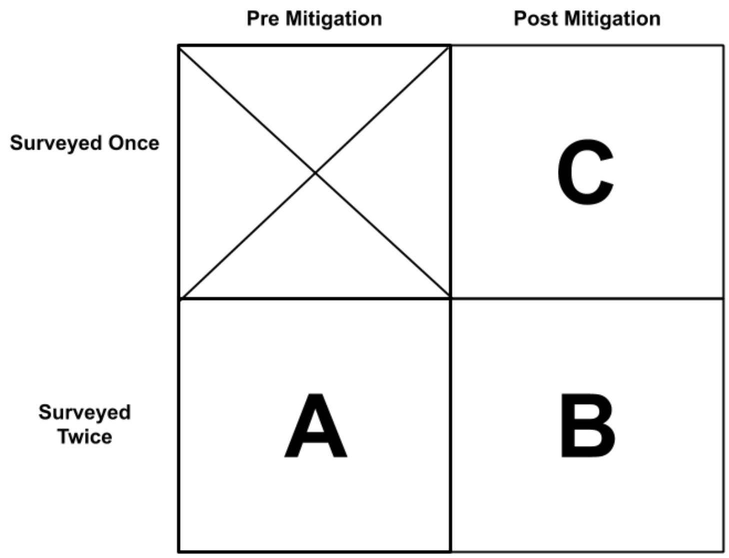

Figure 2: Randomization Design

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

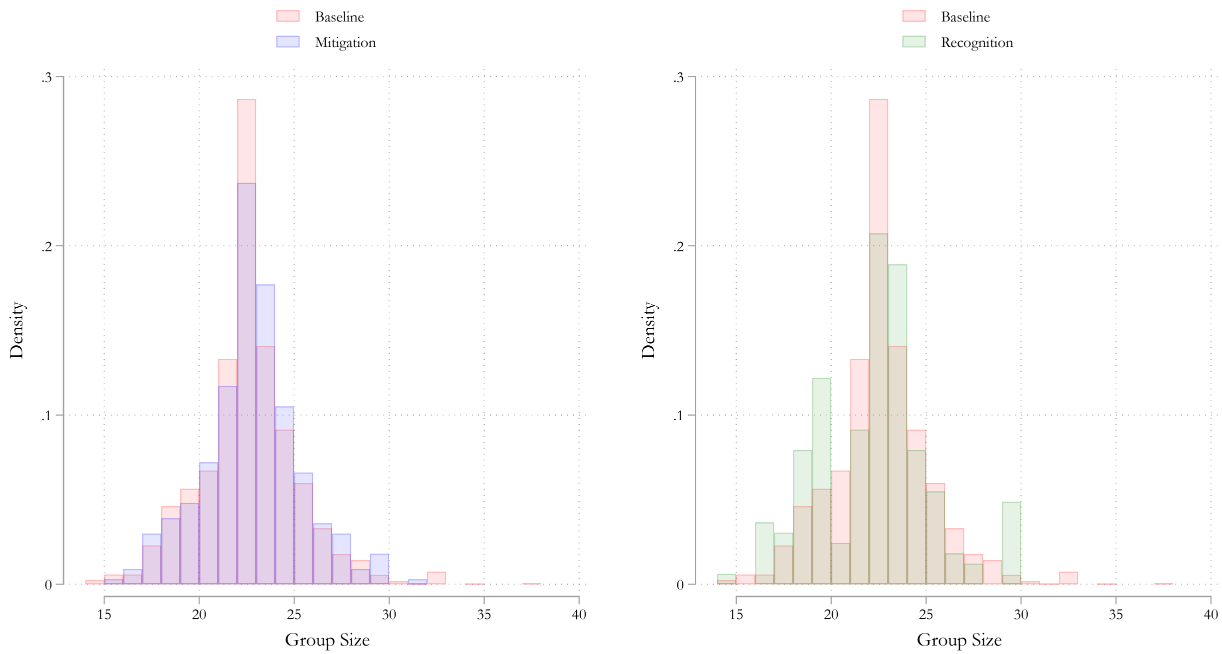

Figure 3: Histogram of Endorsed at Each Round by Size

Notes: These figures present the distribution of borrowers endorsed at each round by group size. The Baseline endorsements round was conducted in November 2018, Mitigation in March 2019, and Recognition in April 2019. Refer to Figure 1 for the intervention and study timeline.

Microfinance Institution Name	Country
BancoSol	Bolivia
Crecer IFD	Bolivia
Acredite Associacao de Microcredito Alto Vale do Itajai	Brazil
Associacao Brasileira para o desenvolvimento da Familia- Banco da Familia	Brazil
Associacao Mineira de Credito Popular	Brazil
Centro de Apoio aos Pequenos Empreendimentos - CEAPE BRASIL	Brazil
Crediamai Agencia de Microcredito	Brazil
CREDIBAHIA-Programa de Microcredito do Estado da Bahia/DESENBAHIA-Agencia de Fomento do Estado da Bahia	Brazil
Icc itabuna Solidaria	Brazil
Instituicao de Credito Solidario - CREDISOL	Brazil
Instituticao Comunitaria de Credito Conquista Solidaria	Brazil
Corporacion de Credito Contactar	Colombia
Fundacion Santo Domingo	Colombia
Mibanco Colombia	Colombia
Banco Popular SA	Honduras
Chaitanya India Fin Credit Pvt Ltd	India
Dvara Kshetriya Gramin Financial Services Private Limited	India
Janakalyan Financial Services Private Limited	India
Muthoot Microfin Limited	India
NABFINS LTD	India
Sangamithra Rural Financial Services	India
Sub-K Impact Solutions Ltd	India
Svasti Microfinance Private Limited	India
UNACCO Financial Services Private Limited	India
Valar Aditi Social Finance Private Limited	India
Wesghats Micro Finance Limited	India
Amextra Sofinco SA de CV SFC	Mexico
Compartamos Banco SA Institucion de Banco Multiple	Mexico
Crediavance Financiera	Mexico
Emprendamos Fin	Mexico
Emprendedores Firme	Mexico
Financiamiento Progresemos, S.A. de C.V. SOFOM E.N.R.	Mexico
Financiera Braxel SA de CV SOFOM ENR	Mexico
Finsostener, SA de V SOFOM, ENR	Mexico
Fortaleza a Mi Futuro SA de CV, SOFOM ENR	Mexico
KapitalMujer SA de CV SOFOM ENR	Mexico
UNIMEX Financiera S.A. de C.V. SOFOM ENR	Mexico
Fundacion Paraguaya	Paraguay
Mibanco	Peru
Banco Ademi	Republica Dominicana

Figure 4: MFIs Responding to Our Survey of Management Practices

B Spillovers onto Joint-Liability Borrowers when Someone Graduates

The results thus far suggest that our partner lender benefited from graduating borrowers endorsed after Mitigation and Recognition. 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 endorsed in survey round S graduate between survey round S and March 2020, we regress

$$y_{it} = \alpha + \beta_S PostS_{it} + \gamma X_i + \delta_i + \phi_t + \lambda_c + \epsilon_{it} \tag{9}$$

The level of observation is borrower by month. Here $PostS_{it}$ is an indicator variable taking the value of 1 if borrower i's group mate has 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.

The coefficient β_S captures any reduction or improvement in the repayment behavior of joint-liability borrowers when one of their group mates who was endorsed in survey round S graduates. We note that we do not have random variation in whether an endorsed borrower graduates. However, our regression includes both month and loan cycle fixed effects, so β_S 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 joint-liability 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 A9 for the full sample of borrowers who graduated (Panel A), borrowers who graduated and were not endorsed in any survey round (Panel B), and borrowers who graduated and were endorsed in baseline, after Mitigation, and after Recognition (Panels C, D, and E). Across the board the point estimates are small, and we can never reject that there are no spillovers on the borrowers who are left behind in joint-liability groups. For the case when the graduated borrower was endorsed after Mitigation or after Recognition, 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.

C The Causal Relationship Between The Cost of Losing a Borrower and Likelihood of Endorsement

In this section we present the full analysis of the causal relationship between the cost of losing a borrower – in terms of forgone compensation as of our baseline in November 2018 – and the likelihood a loan officer endorses her for graduation. This exercise is briefly summarized in Section 5. We will show a strong negative relationship between the cost of losing a borrower and how likely a loan officer is to endorse her at baseline, and we will show that this relationship attenuates after our intervention.

Establishing this relationship entails two challenges. The first regards determining the value that each borrower contributes to a loan officer's compensation. And the second relates to identifying the causal effect of the financial penalty of losing a borrower on the likelihood of endorsement. We discuss each of these challenges in turn.

Determining The Cost of Losing a Borrower

The most direct way to calculate the cost to a loan officer from losing a borrower i is by comparing the loan officer's compensation with her full portfolio to what her compensation would have been if she lost borrower i, utilizing the compensation formula in Appendix Section E. In the regressions that follow we call this $DirectCost$ and it is one of our two key independent variables.

However loan officers' compensation is a piecewise linear function with discontinuous jumps at various levels of portfolio size and risk. Therefore $DirectCost$ is 0 for more than 99% of borrowers. That is, except in the cases where losing a borrower pushes a loan officer over a threshold, this approach disregards borrower-level variation in how close to a threshold a loan officer would be moved if she were to lose a given borrower. Given two borrowers, losing either of whom would not push their loan officer over a compensation threshold, the loan officer may still prefer to lose the one that will push her less near to the threshold. Yet $DirectCost$ treats the cost of losing each of these borrowers as 0.

We circumvent this limitation by computing a second measure of the cost of losing a borrower: the Shapley Value (Shapley, 1953). The Shapley Value is a cooperative game theoretic notion that determines the value any member adds to an arbitrary coalition. In the context of this paper, the Shapley Value for a borrower i is computed by

1. Iterating over all permutations of borrowers in borrower i's loan officer's portfolio
2. For each permutation, calculating the difference between the loan officer's compensation when she manages all borrowers who come before borrower i in the permutation *including borrower* i, and her compensation when she manages all borrowers who come before borrower i in the permutation *excluding borrower* i
3. Averaging borrower i's value-add over all permutations.

While the Shapley Value is well defined by the above formula, computing the exact Shapley Value within our sample would be computationally infeasible. There are 350 borrowers in a typical loan officer's portfolio, and therefore there are 350 factorial permutations over which the borrower's value-add must be evaluated. 350 factorial is approximately 10^{750}; for reference there are approximately 10^{82}atoms in the observable universe.

Fortunately, averages of random variables can be computed precisely with relatively few draws from their distribution. Therefore, observing that the Shapley Value for borrower i is the average value-add of borrower i to the portfolio of borrowers who come before her in a *random* permutation of all borrowers in borrower i's loan officer's portfolio, we can compute the approximate Shapley Value by taking random draws from the distribution of all borrower permutations. We compute the approximate Shapley Value to within 2.5% error by taking 500,000 draws. In contrast to the case of $DirectCost$, nearly 70% of borrowers have a non-zero Shapley Value.

In the regressions to follow, we call this $ShapleyCost$ and it is our second key independent variable.

Identifying the Causal Effect of the Cost of Losing a Borrower On Her Propensity To Be Endorsed

Next comes the question of how to identify the causal effect of the cost of losing a borrower on a loan officer's propensity to endorse that borrower. The challenge arises because features that determine the cost of losing a borrower are correlated with borrower attributes that may inform how suitable she is for a graduation loan. For instance, borrowers with larger loans are costlier to lose but may also be better candidates for graduation. The solution stems from the same observation that gave rise to the challenge above. Namely, loan officer compensation varies discontinuously around certain portfolio-level thresholds. Therefore we use discontinuities based on the number of borrowers that a loan officer manages and the average default in her portfolio to instrument for the cost of losing a given borrower.

Loan officers enjoy jumps in their compensation at 169 and 351 borrowers managed, and when their portfolio falls below 3% at risk.[20] Our instruments are (1) the distance between the number of borrowers in a loan officer's portfolio and 169 and 351 and (2) the distance between the loan officer's average default and 3%. We also include the squares of these distances. The formula by which loan officer compensation is calculated and the details of these instruments are presented in Appendix Section E.

The first stage of our instrumented regression to follow is

$$Cost_i = \alpha + \beta Z_i + \gamma X_i + \epsilon_i \tag{10}$$

Where $Cost_i$ is the cost to borrower i's loan officer from losing borrower i – measured first as $DirectCost_{i,t}$ and second as $ShapleyCost_{i,t}$ using the baseline compensation scheme, Z_i is our vector of threshold instruments for borrower i, and X_i is a vector of controls including those in Table A1, the borrower's tenure with the organization, her loan size, and the amount of her portfolio at risk, which is a summary of her default. We run this regression separately for each survey round. The results are presented in Appendix Tables A6a and A6b. As expected, the closer a loan officer is to a given portfolio-size threshold, the costlier it is to lose her borrowers, and our key first-stage parameters are estimated precisely.[21]

In using these instruments in the regressions to follow, our identifying assumption is that the distance between a loan officer's portfolio and a given threshold is not related to her propensity to endorse a particular borrower except insofar as it influences the cost

[20] Amount at risk is defined to be the pending amount to be repaid if the borrower is at least 7 days late in her repayments. This is the measure that our partner lender tracks to judge their own portfolio performance as well as to compute loan officer compensation.

[21] Across all columns, the first-stage F statistics reject the null of weak instruments at the conventional levels suggested by Stock and Yogo (2005).

of losing a borrower in forgone compensation. This identification assumption may be especially plausible given that our regressions control for all of the variables listed in Table A1, many of which capture observable characteristics relating to a borrower's suitability for endorsement (e.g. her previous loan size, measures of her lateness in repayment, how long she has been a borrower, her business industry, revenues, and profits, and so on). For our identification assumption to be violated, it would need to be that there are systematic differences in the portfolios or characteristics of loan officers (other than their cost of losing a borrower) that relate both to their distance to compensation thresholds and to their propensity to endorse a borrower that are not captured by our rich borrower controls.

Estimates

To estimate the causal effect of the cost of losing a borrower on a loan officer's likelihood to endorse her we run the following regression.

$$y_i = \alpha + \beta Cost_i + \gamma X_i + \epsilon_i \tag{11}$$

where y_i is an indicator for whether borrower i was endorsed, and the rest of the variables are defined as in Specification 10. Both measures of cost are normalized by their standard deviations. To account for the endogeneity of $Cost_i$ we estimate Specification 11 via two stage least squares, where our first stage is described in the previous section. Because our sample comprises the universe of borrowers to whom our lender could offer graduation loans, we cluster our regressions at the borrower level. The results are presented in Table A7. Panel A corresponds to the relationship at baseline, Panel B corresponds to the relationship after Mitigation, and Panel C corresponds to the relationship after Recognition. Columns 1 and 2 correspond to $DirectCost$ and columns 3 and 4 correspond to $ShapleyCost$. As expected, the results indicate that loan officers are likelier to endorse borrowers with higher loan sizes and lower default.

Two important patterns emerge. First, at baseline there is a strong negative relationship between the cost of losing a borrower and the likelihood a loan officer endorses her. A one standard deviation increase in the $DirectCost$ of losing a borrower corresponds to a 0.8 [SE: 0.4] to 0.9 [SE: 0.4] percentage point decline in the likelihood of endorsing a borrower (Panel A columns 1 and 2). Similarly, a one standard deviation increase in the $ShapleyCost$ of losing a borrower corresponds to a 0.8 [SE: 0.2] percentage point decline in the likelihood of endorsing a borrower (Panel A columns 3 and 4). Given that the baseline probability of endorsement across the whole sample was 5.9 percentage points per borrower, increasing either measure of cost by 1 standard deviation causes a roughly 14-15% drop in the likelihood of endorsement.

The second important pattern is that the relationship between the costliness to lose a borrower and the likelihood that a borrower is endorsed diminishes across the survey rounds, as the two new compensation schemes are introduced. Indeed, in all cases the coefficients corresponding to the Mitigation and Recognition rounds are statistically significantly smaller (at the 5 or 1 percent level) than the coefficients corresponding to the baseline survey round. This suggests that loan officers have internalized that our compensation shifts disproportionately reduce the cost of endorsing borrowers that were more important to their compensation in the baseline scheme. In fact, columns 1 and 2 of Panel C indicate that the relationship between $DirectCost$ and likelihood of endorsement has *reversed* by the $PostRecognition$ survey, which is consistent with possibility that loan officers were disproportionately withholding endorsements of borrowers who were costliest to lose prior to the compensation shift and therefore that these borrowers were disproportionately endorsed after the shift.

Table A8 presents the OLS estimates of Specification 11. For the most part the results are qualitatively similar to the instrumental variable estimates; the cost of losing a borrower is negatively related to the likelihood of endorsement in almost all cases, and the estimates are statistically significantly smaller for the Mitigation and Recognition rounds in most cases.

D Appendix Tables

Table A1: Randomization Check

	All Borrowers	Control (Pre Mitigation) Sample	Treatment Sample
	Mean	Mean	Difference from Control Sample
	(1)	(2)	(3)
Panel A: Borrower Characteristics			
Age	45.683	45.743	-0.111
	[13.170]	[13.149]	(0.262)
Gender: Male	0.199	0.196	0.005
	[0.399]	[0.397]	(0.008)
Married	0.391	0.388	0.005
	[0.488]	[0.487]	(0.010)
HH Size	3.664	3.643	0.040
	[1.587]	[1.591]	(0.039)
Education: Secondary and Above	0.630	0.627	0.008
	[0.483]	[0.484]	(0.009)
No. of Non-HH Workers	0.120	0.129	-0.017*
	[0.970]	[1.073]	(0.009)
Sector: Manufacturing	0.289	0.291	-0.004
	[0.453]	[0.454]	(0.005)
Sector: Retail	0.582	0.581	0.002
	[0.493]	[0.493]	(0.007)
Sector: Services	0.125	0.123	0.003
	[0.331]	[0.329]	(0.005)
Sector: Agriculture	0.004	0.004	-0.001
	[0.065]	[0.066]	(0.001)
Monthly Business Revenues (USD)	1035.145	1039.063	-5.914
	[760.302]	[757.278]	(20.722)
Monthly Business Profits (USD)	687.351	687.942	1.037
	[518.640]	[518.076]	(15.437)
Group Size	21.654	21.626	0.039
	[2.753]	[2.657]	(0.135)
Borrower Cycle	8.033	8.103	-0.126
	[7.189]	[7.176]	(0.295)
Amount Borrowed	859.673	865.402	-11.398
	[524.793]	[522.898]	(18.522)
Days Late	0.423	0.431	-0.112
	[4.345]	[4.442]	(0.106)
Amount Late	2.798	2.798	-0.658
	[26.658]	[26.996]	(0.572)
P-Value for Joint Difference F test:			0.689
Observations	81,220	39,381	77,508
Panel B: Loan Officer Characteristics			
Number of Borrowers	337.436	344.957	-6.772
	[81.951]	[74.377]	(10.109)
Portfolio (USD)	272914.844	283918.469	-14843.721
	[92280.797]	[88034.508]	(11880.571)
Total Amount Late (USD)	892.191	921.410	-243.490
	[1848.535]	[1628.729]	(182.922)
Fraction of Borrowers in Portfolio Endorsed at Baseline	0.058	0.063	-0.008
	[0.070]	[0.082]	(0.009)
P-Value for Joint Difference F test:			0.315
Observations	243	115	229

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 Mitigation survey round in February 2019, just before the Mitigation scheme was announced. 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 Mitigation 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 Endorsements - Additional Controls

	Total Cumulative Endorsements					
	Between Officers		All Officers		All Officers	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1: Post Mitigation	1.092***	1.215*	1.338***	1.570***	1.317***	1.539***
	(0.283)	(0.630)	(0.271)	(0.498)	(0.277)	(0.538)
β_2: Post Recognition					2.151***	2.415***
					(0.341)	(0.679)
γ_1: Number of LO's that joined in the same period	-0.129	-0.177	-0.121	-0.172	-0.215	-0.299
	(0.145)	(0.113)	(0.128)	(0.123)	(0.168)	(0.183)
γ_2: Years in MFI	-0.007	0.025	-0.051	0.010	-0.070	0.014
	(0.043)	(0.044)	(0.058)	(0.057)	(0.079)	(0.071)
γ_3: Post Mitigation $\times$ LO's that joined in the same period		0.070		0.063		0.140
		(0.176)		(0.158)		(0.184)
γ_4: Post Mitigation $\times$ Years in MFI		-0.060		-0.087		-0.116
		(0.084)		(0.068)		(0.079)
γ_5: Post Recognition $\times$ LO's that joined in the same period						0.043
						(0.218)
γ_6: Post Recognition $\times$ Years in MFI						-0.088
						(0.101)
P-value for F Test: $\beta_1 = \beta_2$					0.000	0.008
Mean: Endorsements pre Mitigation	0.187	0.187	0.187	0.187	0.187	0.187
	[0.862]	[0.862]	[0.862]	[0.862]	[0.862]	[0.862]
Mean: Endorsements at Baseline	20.437	20.437	20.924	20.924	20.914	20.914
	[27.007]	[27.007]	[28.601]	[28.601]	[28.201]	[28.201]
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**: This table replicates Table 1 with the addition of two additional controls: i) The number of Loan Officers that joined their office within the same period, and, ii) The number of years the Loan Officer has worked at the microfinance institution. Standard errors are in parentheses. Standard errors are clustered at the loan officer level. Standard deviations are in brackets. Columns (1)-(4) only include the February and March survey waves, and Columns (5)-(6) include the pre-mitigation round in February, the post mitigation round in March, and the post recognition round in April. Pre-mitigation is the omitted group in all regressions. Loan officer controls include the total number of endorsements made in November Baseline, size of total loan portfolio in November 2018, and number of borrowers in the loan officer's portfolio in November 2018. Branch fixed effects are included in all columns. **Outcome variable**: Columns (1)-(6) report results on the total cumulative number of endorsements made by a loan officer by each survey round.

Table A3: Do Endorsements Predict Default on Join-Liability Loans? - Limiting the Repayment Window before the Covid-19 Shutdown

	Late $\geq$ 15 days		Late $\geq$ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Endorsements								
$\beta_{Baseline}$: Endorsed at Baseline	-0.007	-0.005	-0.012	-0.011	-0.005	-0.004	-11.941	-9.519
	(0.016)	(0.015)	(0.008)	(0.008)	(0.020)	(0.020)	(44.937)	(44.844)
Mean: Not Endorsed	0.078	0.078	0.031	0.031	0.061	0.061	128.270	128.270
	[0.268]	[0.268]	[0.175]	[0.175]	[0.240]	[0.240]	[543.462]	[543.462]
Lasso Controls		X		X		X		X
Number of Borrowers	721	721	721	721	721	721	721	721
Observations	25299	25299	25299	25299	721	721	721	721
Panel B: Mitigation Endorsements								
$\beta_{Mitigation}$: Endorsed at Mitigation	-0.042**	-0.042**	-0.018***	-0.018***	-0.024***	-0.024***	-49.978***	-49.978***
	(0.017)	(0.017)	(0.006)	(0.006)	(0.007)	(0.007)	(16.525)	(16.507)
Mean: Not Endorsed	0.053	0.053	0.017	0.017	0.024	0.024	49.978	49.978
	[0.224]	[0.224]	[0.130]	[0.130]	[0.154]	[0.154]	[351.348]	[351.348]
Lasso Controls		X		X		X		X
Number of Borrowers	467	467	467	467	467	467	467	467
Observations	13299	13299	13299	13299	467	467	467	467
Panel C: Recognition Endorsements								
$\beta_{Recognition}$: Endorsed at Recognition	0.019	0.019	-0.018**	-0.018**	-0.018***	-0.018***	-36.243**	-36.243**
	(0.048)	(0.048)	(0.007)	(0.007)	(0.007)	(0.007)	(15.103)	(15.084)
Mean: Not Endorsed	0.048	0.048	0.015	0.015	0.018	0.018	36.243	36.243
	[0.214]	[0.214]	[0.120]	[0.120]	[0.132]	[0.132]	[299.796]	[299.796]
Lasso Controls		X		X		X		X
Number of Borrowers	405	405	405	405	405	405	405	405
Observations	10321	10321	10321	10321	405	405	405	405
Panel D: Mitigation or Recognition Endorsements								
β_{MoR}: Endorsed at Mitigation or Recognition	-0.022	-0.022	-0.019***	-0.019***	-0.024***	-0.024***	-49.978***	-49.978***
	(0.024)	(0.023)	(0.006)	(0.006)	(0.007)	(0.007)	(16.524)	(16.507)
Mean: Not Endorsed	0.053	0.053	0.017	0.017	0.024	0.024	49.978	49.978
	[0.224]	[0.224]	[0.130]	[0.130]	[0.154]	[0.154]	[351.348]	[351.348]
Lasso Controls		X		X		X		X
Number of Borrowers	477	477	477	477	477	477	477	477
Observations	13640	13640	13640	13640	477	477	477	477
P-Value for F test:								
$\beta_{Baseline} = \beta_{Mitigation}$	0.089	0.089	0.499	0.499	0.322	0.322	0.374	0.374
$\beta_{Baseline} = \beta_{Recognition}$	0.601	0.601	0.560	0.560	0.527	0.527	0.578	0.578
$\beta_{Mitigation} = \beta_{Recognition}$	0.213	0.213	0.932	0.932	0.138	0.138	0.177	0.177
$\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.586	0.586	0.420	0.420	0.322	0.322	0.374	0.374

Notes: **Specification**: This table implements Specification 6. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. 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, endorsed borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers endorsed at that given round and those never endorsed. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Only borrowers endorsed at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never endorsed at any round. The sample in every panel is limited to the first graduation loan that is disbursed after the respective survey. Data utilized comes from reports between November 2018 and February 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls for average days late before Baseline, and demographic and business characteristics from Table A1. Tests of equality of Baseline and Post Mitigation, Baseline and Post Recognition, Post Mitigation and Post Recognition, and Baseline and Post Mitigation or Post Recognition 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 endorsement wave, up to February 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 endorsement wave, up to February 2020. Columns (5)-(6) report results on an indicator variable for ever defaulted on a Graduation loan in the months after each endorsement wave, up to February 2020. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each endorsement wave, up to February 2020.

Table A4: Does Strength of Endorsements Predict Repayment 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 Endorsements								
$\beta_{Baseline}$: Endorsed at Baseline	0.002	0.002	-0.001	-0.001	0.004	0.005	3.989	3.989
	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.009)	(19.173)	(19.146)
Mean: Not Endorsed	0.183	0.183	0.098	0.098	0.374	0.374	559.170	559.170
	[0.387]	[0.387]	[0.297]	[0.297]	[0.484]	[0.484]	[1019.316]	[1019.316]
Lasso Controls		X		X		X		X
Number of Borrowers	719	719	719	719	719	719	719	719
Observations	44458	44458	44458	44458	719	719	719	719
Panel B: Mitigation Endorsements								
$\beta_{Mitigation}$: Endorsed at Mitigation	-0.027***	-0.027***	-0.015**	-0.014*	-0.090***	-0.089***	-148.082***	-147.424***
	(0.010)	(0.010)	(0.007)	(0.008)	(0.007)	(0.007)	(15.292)	(15.178)
Mean: Not Endorsed	0.191	0.191	0.101	0.101	0.358	0.358	590.429	590.429
	[0.393]	[0.393]	[0.302]	[0.302]	[0.480]	[0.480]	[1106.442]	[1106.442]
Lasso Controls		X		X		X		X
Number of Borrowers	466	466	466	466	466	466	466	466
Observations	29900	29900	29900	29900	466	466	466	466
Panel C: Recognition Endorsements								
$\beta_{Recognition}$: Endorsed at Recognition	0.002	0.002	-0.003	-0.003	0.017	0.016	9.130	9.130
	(0.014)	(0.014)	(0.009)	(0.009)	(0.036)	(0.036)	(69.518)	(69.346)
Mean: Not Endorsed	0.198	0.198	0.105	0.105	0.362	0.362	623.459	623.459
	[0.398]	[0.398]	[0.307]	[0.307]	[0.481]	[0.481]	[1143.548]	[1143.548]
Lasso Controls		X		X		X		X
Number of Borrowers	405	405	405	405	405	405	405	405
Observations	25807	25807	25807	25807	405	405	405	405
Panel D: Mitigation or Recognition Endorsements								
β_{MoR}: Endorsed at Mitigation or Recognition	0.003	0.003	-0.002	-0.002	0.018	0.017	16.210	13.628
	(0.014)	(0.014)	(0.009)	(0.009)	(0.036)	(0.036)	(69.240)	(69.215)
Mean: Not Endorsed	0.191	0.191	0.101	0.101	0.358	0.358	590.429	590.429
	[0.393]	[0.393]	[0.302]	[0.302]	[0.480]	[0.480]	[1106.442]	[1106.442]
Lasso Controls		X		X		X		X
Number of Borrowers	462	462	462	462	462	462	462	462
Observations	29569	29569	29569	29569	462	462	462	462
P-Value for F test:								
$\beta_{Baseline} = \beta_{Mitigation}$	0.005	0.005	0.066	0.066	0.000	0.000	0.000	0.000
$\beta_{Baseline} = \beta_{Recognition}$	0.997	0.997	0.831	0.831	0.718	0.714	0.942	0.941
$\beta_{Mitigation} = \beta_{Recognition}$	0.082	0.082	0.283	0.283	0.003	0.003	0.022	0.022
$\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.937	0.937	0.877	0.877	0.702	0.698	0.862	0.861

Notes: **Specification**: This table implements Specification 6. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. 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. Strength of Endorsement for each round is a continuous variable that contains the confidence value selected by the loan officer for each endorsement, on a scale ranging from 0 to 5 (the higher the value, the higher the confidence on the endorsement). For all panels, endorsed borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers endorsed at that given round and those never endorsed. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Only borrowers endorsed at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never endorsed at any round. The sample in every panel is limited to the first completed graduation loan that is disbursed after the respective survey. Data utilized comes from reports between November 2018 and October 2022. Odd columns don't include any control variables. Even columns include double-post lasso controls for average days late before Baseline, and demographic and business characteristics from Table A1. Tests of equality of 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 endorsement wave, up to October 2022. 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 endorsement wave, up to October 2022. Columns (5)-(6) report results on an indicator variable for ever defaulted on a Graduation loan in the months after each endorsement wave, up to October 2022. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each endorsement wave, up to October 2022.

Table A5: Does Strength of Endorsements Predict Repayment on Joint-Liability Loans?

	Late $\geq$ 15 days		Late $\geq$ 90 days		Defaulted		Amount Defaulted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Endorsements								
$\beta_{Baseline}$: Endorsed at Baseline	-0.002***	-0.000***	-0.000***	-0.000*	-0.002***	-0.001***	-0.193	-0.536
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.351)	(0.368)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.025	0.025	11.741	11.741
	[0.115]	[0.115]	[0.044]	[0.044]	[0.156]	[0.156]	[99.888]	[99.888]
Lasso Controls		X		X		X		X
Number of Borrowers	75275	75275	75275	75275	75275	75275	75275	75275
Observations	3341351	3341351	3341351	3341351	75275	75275	75275	75275
Panel B: Mitigation Endorsements								
$\beta_{Mitigation}$: Endorsed at Mitigation	-0.002***	-0.002***	-0.000***	-0.000***	-0.004***	-0.004***	-2.222***	-2.620***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.657)	(0.670)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.027	0.027	12.869	12.869
	[0.111]	[0.111]	[0.043]	[0.043]	[0.163]	[0.163]	[104.504]	[104.504]
Lasso Controls		X		X		X		X
Number of Borrowers	64797	64797	64797	64797	64797	64797	64797	64797
Observations	2520606	2520606	2520606	2520606	64797	64797	64797	64797
Panel C: Recognition Endorsements								
$\beta_{Recognition}$: Endorsed at Recognition	-0.001*	-0.001*	-0.000	-0.000	-0.005***	-0.004**	-1.857	-2.041*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(1.168)	(1.181)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.029	0.029	13.616	13.616
	[0.113]	[0.113]	[0.045]	[0.045]	[0.168]	[0.168]	[107.458]	[107.458]
Lasso Controls		X		X		X		X
Number of Borrowers	61081	61081	61081	61081	61081	61081	61081	61081
Observations	2119964	2119964	2119964	2119964	61081	61081	61081	61081
Panel D: Mitigation or Recognition Endorsements								
β_{MoR}: Endorsed at Mitigation or Recognition	-0.002***	-0.001*	-0.000	-0.000	-0.005***	-0.004**	-1.718	-1.977*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(1.131)	(1.144)
Mean: Not Endorsed	0.013	0.013	0.002	0.002	0.027	0.027	12.869	12.869
	[0.111]	[0.111]	[0.043]	[0.043]	[0.163]	[0.163]	[104.504]	[104.504]
Lasso Controls		X		X		X		X
Number of Borrowers	64636	64636	64636	64636	64636	64636	64636	64636
Observations	2513377	2513377	2513377	2513377	64636	64636	64636	64636
P-Value for F test:								
$\beta_{Baseline} = \beta_{Mitigation}$	0.318	0.001	0.064	0.000	0.082	0.023	0.006	0.023
$\beta_{Baseline} = \beta_{Recognition}$	0.779	0.238	0.698	0.707	0.092	0.034	0.170	0.281
$\beta_{Mitigation} = \beta_{Recognition}$	0.425	0.425	0.285	0.285	0.824	0.824	0.784	0.784
$\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.968	0.094	0.797	0.525	0.124	0.047	0.195	0.321

Notes: **Specification**: : This table implements Specification 7. Standard errors are in parentheses, clustered at the borrower level. Standard deviations are in brackets. 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. Strength of Endorsement for each round is a continuous variable that contains the confidence value selected by the loan officer for each endorsement, on a scale ranging from 0 to 5 (the higher the value, the higher the confidence on the endorsement). For all panels, endorsed borrowers in other rounds are excluded from each round regression, so the sample for each round comprises borrowers endorsed at that given round and those never endorsed. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Only borrowers endorsed at Baseline are excluded from Panel D. The omitted group in all panels is borrowers who were never endorsed at any round. The sample in every panel is limited to the completed joint liability loans that are disbursed after the respective survey. Data utilized comes from reports between November 2018 and February 2020. Odd columns don't include any control variables. Even columns include double-post lasso controls for average days late before Baseline, and demographic and business characteristics from Table A1. Tests of equality of 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 endorsement wave, up to February 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 endorsement wave, up to February 2020. Columns (5)-(6) report results on an indicator variable for ever defaulted on a Graduation loan in the months after each endorsement wave, up to February 2020. Columns (7)-(8) report results on total amount defaulted for each borrower in the months after each endorsement wave, up to February 2020.

Table A6a: First Stage: Impact of the Cost of Losing a Borrower on Likelihood of Endorsements (Direct Cost)

	Direct Cost (USD)							
	Baseline		Mitigation		Recognition		Mitigation or Recognition	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ_1: Principal (USD)	0.004	-0.004	0.005	-0.006	0.005	-0.006	0.005	-0.006
	(0.005)	(0.009)	(0.005)	(0.010)	(0.005)	(0.010)	(0.005)	(0.010)
γ_2: Amount at Risk (USD)	-0.107***	-0.138***	-0.109***	-0.141***	-0.109***	-0.141***	-0.109***	-0.141***
	(0.019)	(0.023)	(0.019)	(0.024)	(0.019)	(0.024)	(0.019)	(0.024)
γ_3: Borrower Loan Cycle	-0.013***	-0.045***	-0.013***	-0.047***	-0.013***	-0.047***	-0.013***	-0.046***
	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)
β_1: Below 169	-0.007***	-0.008***	-0.007***	-0.008***	-0.007***	-0.008***	-0.007***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β_2: Below 169 Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3: Below 169 Dummy	-0.248***	-0.246***	-0.248***	-0.250***	-0.249***	-0.251***	-0.248***	-0.249***
	(0.030)	(0.031)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)
β_4: Below 351	-0.018***	-0.018***	-0.019***	-0.018***	-0.019***	-0.019***	-0.019***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β_5: Below 351 Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_6: Below 351 Dummy	-0.539***	-0.530***	-0.555***	-0.546***	-0.556***	-0.547***	-0.554***	-0.544***
	(0.029)	(0.029)	(0.031)	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)
β_7: Above 351	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_8: Above 351 Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_9: Below 3%	0.574***	0.577***	0.610***	0.614***	0.610***	0.614***	0.608***	0.612***
	(0.033)	(0.032)	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)	(0.034)
β_{10}: Below 3% Squared	-0.151***	-0.150***	-0.161***	-0.160***	-0.161***	-0.160***	-0.160***	-0.159***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
β_{11}: Below 3% Dummy	0.631***	0.638***	0.696***	0.706***	0.695***	0.704***	0.693***	0.703***
	(0.076)	(0.070)	(0.080)	(0.073)	(0.080)	(0.073)	(0.080)	(0.073)
β_{12}: Above 3%	0.177***	0.178***	0.179***	0.180***	0.180***	0.181***	0.179***	0.180***
	(0.021)	(0.019)	(0.021)	(0.019)	(0.021)	(0.019)	(0.021)	(0.019)
β_{13}: Above 3% Squared	-0.014***	-0.015***	-0.014***	-0.015***	-0.014***	-0.015***	-0.014***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Borrower Controls		X		X		X		X
R-Squared	0.049	0.055	0.051	0.057	0.051	0.057	0.051	0.057
Fst	30.45	30.84	29.90	30.32	29.91	30.32	29.90	30.31
Number of Borrowers	65127	65127	61389	61389	61267	61267	61534	61534
Observations	65127	65127	61389	61389	61267	61267	61534	61534

Notes: **Specification**: This table implements Specification 10. This is the first stage of columns (1)-(2) on Table A7. The unit of observation is the borrower. Robust standard errors are in parentheses. We exclude borrowers from 9 loan officers who have not worked long enough with our partner lender to be eligible for a bonus. All regressions include the following instruments: distance to 169 borrowers from below and its square; distance to 351 borrowers from below and its square; distance to 351 borrowers from above and its square; distance to 3% lateness indicator from below and its square; and distance to 3% lateness indicator from above and its square. Dummy variables are also included to control for loan officers to whom an instrument does not apply. Finally, the following variables are also included as controls: Principal : Loan amount given to the borrower; Amount at Risk : the complete pending amount if the borrower has 7 or more days late (and zero otherwise); Borrower Loan Cycle : the number of cycles that the borrower has been with our partner lender; controls for average days late before Baseline, and demographic and business characteristics from Table A1. **Outcome variable**: Columns (1)-(8) report results on Direct Cost (USD), which is the amount that the officer would have lost if the borrower had graduated in November 2018. Borrowers who are endorsed in other rounds are excluded from the regressions. So borrowers endorsed at Mitigation or Recognition are excluded from columns 1 and 2. Borrowers endorsed at Baseline or Recognition are excluded from columns 3 and 4. Borrowers endorsed at Baseline or Mitigation are excluded from columns 5 and 6. Only borrowers endorsed at Baseline are excluded from columns 7 and 8.

Table A6b: First Stage: Impact of the Cost of Losing a Borrower on Likelihood of Endorsements (Shapley Cost)

	Shapley Cost (USD)							
	Baseline		Mitigation		Recognition		Mitigation or Recognition	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ_1: Principal (USD)	0.194***	0.210***	0.184***	0.204***	0.184***	0.204***	0.183***	0.203***
	(0.004)	(0.008)	(0.004)	(0.009)	(0.004)	(0.009)	(0.004)	(0.009)
γ_2: Amount at Risk (USD)	-0.294***	-0.339***	-0.282***	-0.325***	-0.282***	-0.325***	-0.282***	-0.325***
	(0.028)	(0.034)	(0.027)	(0.033)	(0.027)	(0.033)	(0.027)	(0.033)
γ_3: Borrower Loan Cycle	-0.042***	-0.028***	-0.037***	-0.024***	-0.038***	-0.024***	-0.037***	-0.023***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
β_1: Below 169	-0.022***	-0.021***	-0.022***	-0.021***	-0.022***	-0.021***	-0.022***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
β_2: Below 169 Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3: Below 169 Dummy	0.431***	0.417***	0.444***	0.434***	0.443***	0.432***	0.447***	0.436***
	(0.088)	(0.092)	(0.087)	(0.091)	(0.087)	(0.091)	(0.087)	(0.091)
β_4: Below 351	-0.008***	-0.007***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_5: Below 351 Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_6: Below 351 Dummy	0.586***	0.581***	0.592***	0.587***	0.595***	0.590***	0.593***	0.588***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
β_7: Above 351	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β_8: Above 351 Squared	0.000*	0.000	0.000**	0.000*	0.000**	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_9: Below 3%	0.591***	0.632***	0.605***	0.642***	0.596***	0.633***	0.602***	0.639***
	(0.039)	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)	(0.037)
β_{10}: Below 3% Squared	-0.165***	-0.173***	-0.168***	-0.175***	-0.165***	-0.172***	-0.167***	-0.174***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
β_{11}: Below 3% Dummy	-0.281*	-0.119	-0.290**	-0.140	-0.298**	-0.146	-0.284*	-0.132
	(0.152)	(0.150)	(0.146)	(0.145)	(0.146)	(0.145)	(0.145)	(0.145)
β_{12}: Above 3%	0.221***	0.201***	0.237***	0.217***	0.234***	0.214***	0.234***	0.214***
	(0.039)	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)	(0.037)
β_{13}: Above 3% Squared	-0.014***	-0.013***	-0.015***	-0.014***	-0.015***	-0.014***	-0.015***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Borrower Controls		X		X		X		X
R-Squared	0.246	0.255	0.254	0.263	0.254	0.262	0.253	0.262
Fst	2,017.28	1,975.92	2,002.86	1,969.60	1,993.60	1,965.93	2,015.51	1,983.45
Number of Borrowers	65127	65127	61389	61389	61267	61267	61534	61534
Observations	65127	65127	61389	61389	61267	61267	61534	61534

Notes: **Specification**: This table implements Specification 10. This is the first stage of columns (3)-(4) on Table A7. The unit of observation is the borrower. Robust standard errors are in parentheses. We exclude borrowers from 9 loan officers who have not worked long enough with our partner lender to be eligible for a bonus. All regressions include the following instruments: distance to 169 borrowers from below and its square; distance to 351 borrowers from below and its square; distance to 351 borrowers from above and its square; distance to 3% lateness indicator from below and its square; and distance to 3% lateness indicator from above and its square. Dummy variables are also included to control for loan officers to whom an instrument does not apply. Finally, the following normalized variables are also included as controls: Principal : Loan amount given to the borrower; Amount at Risk : the complete pending amount if the borrower has 7 or more days late (and zero otherwise); Borrower Loan Cycle : the number of cycles that the borrower has been with our partner lender; controls for average days late before Baseline, and demographic and business characteristics from Table A1. **Outcome variable**: Columns (1)-(8) report results on the Shapley Cost (USD), which is a measure of the value of a borrower to a loan officer's portfolio. See Section E for details on the construction of this variable. Borrowers who are endorsed in other rounds are excluded from the regressions. So borrowers endorsed at Mitigation or Recognition are excluded from columns 1 and 2. Borrowers endorsed at Baseline or Recognition are excluded from columns 3 and 4. Borrowers endorsed at Baseline or Mitigation are excluded from columns 5 and 6. Only borrowers endorsed at Baseline are excluded from columns 7 and 8.

Table A7: Impact of the Cost of Losing a Borrower on Likelihood of Endorsements

	Direct Cost		Shapley Cost	
	(1)	(2)	(3)	(4)
Panel A: Baseline Endorsements				
β: Cost (USD)	-0.010**	-0.011**	-0.008***	-0.009***
	(0.005)	(0.005)	(0.003)	(0.003)
γ_1: Principal (USD)	0.039***	0.025***	0.040***	0.027***
	(0.001)	(0.003)	(0.001)	(0.003)
γ_2: Amount at Risk (USD)	-0.005***	-0.004***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
γ_3: Borrower Loan Cycle	0.007***	-0.000	0.007***	0.000
	(0.001)	(0.002)	(0.001)	(0.002)
Number of Borrowers	65127	65127	65127	65127
Panel B: Mitigation Endorsements				
β: Cost (USD)	0.000	0.000	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
γ_1: Principal (USD)	0.003***	0.002**	0.003***	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)
γ_2: Amount at Risk (USD)	-0.000	-0.000	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_3: Borrower Loan Cycle	-0.000	-0.001*	-0.000	-0.001*
	(0.000)	(0.001)	(0.000)	(0.001)
Number of Borrowers	61389	61389	61389	61389
Panel C: Recognition Endorsements				
β: Cost (USD)	0.004***	0.004***	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
γ_1: Principal (USD)	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)
γ_2: Amount at Risk (USD)	0.000	0.000**	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
γ_3: Borrower Loan Cycle	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Borrowers	61267	61267	61267	61267
Panel D: Mitigation or Recognition Endorsements				
β: Cost (USD)	0.004**	0.004**	-0.003***	-0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
γ_1: Principal (USD)	0.004***	0.003***	0.005***	0.004***
	(0.000)	(0.001)	(0.000)	(0.001)
γ_2: Amount at Risk (USD)	-0.000	0.000	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_3: Borrower Loan Cycle	0.000	-0.001	-0.000	-0.001**
	(0.000)	(0.001)	(0.000)	(0.001)
Number of Borrowers	61534	61534	61534	61534
P-value for F Test:				
$\beta_{Baseline} = \beta_{Mitigation}$	0.030	0.023	0.011	0.008
$\beta_{Baseline} = \beta_{Recognition}$	0.003	0.002	0.005	0.002
$\beta_{Mitigation} = \beta_{Recognition}$	0.016	0.014	0.539	0.413
$\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.003	0.002	0.033	0.024

Notes: **Specification**: This table implements Specification 11. The first stages of the IV Specifications of Panel A and B can be found on Table A6a and Table A6b, respectively. The unit of observation is the borrower. Robust standard errors are in parentheses. Direct Cost (USD) is the amount that the officer would have lost if the borrower had graduated in November 2018. Shapley Cost (USD) is an alternative measure of the value of a borrower to a loan officer's portfolio. See Section E for details on the construction of these Cost variables. Columns (1) and (2) report results using Direct Cost as independent variable, whereas columns (3) and (4) report results using the Shapley Cost. For each panel, the sample comprisses borrowers endorsed in that round and those never endoresed. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Panel D pools Panel B and C. Thus, only borrowers endorsed at Baseline are excluded from Panel D. We exclude borrowers from 9 loan officers who have not worked long enough with our partner lender to be eligible for a bonus. The first stage regression includes the following instruments: distance to 169 borrowers from below and its square; distance to 351 borrowers from below and its square; distance to 351 borrowers from above and its square; distance to 3% lateness indicator from below and its square; and distance to 3% lateness indicator from above and its square. Dummy variables are also included to control for loan officers to whom an instrument does not apply. The second stage regression also includes the following standarized variables as controls: Principal : Loan amount given to the borrower; Amount at Risk : the complete pending amount if the borrower has 7 or more days late (and zero otherwise); Borrower Loan Cycle : the number of cycles that the borrower has been with our partner lender; controls for average days late before Baseline, and demographic and business characteristics from Table A1. **Outcome variable**: For every Panel, Columns (1)-(4) report results on an standarized indicator variable that equals 1 for being endorsed at a given round, and 0 if never endorsed.

Table A8: Impact of the Cost of Losing a Borrower on Likelihood of Endorsements (Ordinary Least Squares)

	Direct Cost		Shapley Cost	
	(1)	(2)	(3)	(4)
Panel A: Baseline Endorsements				
β: Cost (USD)	-0.003***	-0.003***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
γ_1: Principal (USD)	0.038***	0.026***	0.037***	0.024***
	(0.001)	(0.003)	(0.001)	(0.003)
γ_2: Amount at Risk (USD)	-0.004***	-0.003***	-0.002***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
γ_3: Borrower Loan Cycle	0.006***	0.000	0.007***	0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Number of Borrowers	67205	67205	67205	67205
Observations	67205	67205	67205	67205
Panel B: Mitigation Endorsements				
β: Cost (USD)	-0.000***	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
γ_1: Principal (USD)	0.003***	0.002**	0.003***	0.002**
	(0.000)	(0.001)	(0.000)	(0.001)
γ_2: Amount at Risk (USD)	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
γ_3: Borrower Loan Cycle	0.000	-0.001	0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Number of Borrowers	63415	63415	63415	63415
Observations	63415	63415	63415	63415
Panel C: Recognition Endorsements				
β: Cost (USD)	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_1: Principal (USD)	0.001***	0.001**	0.002***	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)
γ_2: Amount at Risk (USD)	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_3: Borrower Loan Cycle	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Borrowers	63285	63285	63285	63285
Observations	63285	63285	63285	63285
Panel D: Mitigation or Recognition Endorsements				
β: Cost (USD)	-0.001***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_1: Principal (USD)	0.004***	0.003***	0.004***	0.004***
	(0.000)	(0.001)	(0.000)	(0.001)
γ_2: Amount at Risk (USD)	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
γ_3: Borrower Loan Cycle	0.000	-0.001	0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
P-value for F Test: $\beta_{Baseline} = \beta_{Mitigation}$	0.000	0.138	0.000	0.296
P-value for F Test: $\beta_{Baseline} = \beta_{Recognition}$	0.000	0.057	0.000	0.158
P-value for F Test: $\beta_{Mitigation} = \beta_{Recognition}$	0.000	0.548	0.000	0.576
P-value for F Test: $\beta_{Baseline} = \beta_{Mitigation \vee Recognition}$	0.000	0.215	0.000	0.442
Borrower Controls		X		X
Number of Borrowers	63566	65127	63566	63566
Observations	63566	63566	63566	63566

Notes: **Specification**: This table implements Specification 11 by Ordinary Least Squares. The unit of observation is the borrower. Robust standard errors are in parentheses. Independent variables are normalized, therefore, so that coefficients are expressed in standard deviations. Direct Cost (USD) is the amount that the officer would have lost if the borrower had graduated in November 2018. Shapley Cost (USD) is an alternative measure of the value of a borrower to a loan officer's portfolio. See Section E for details on the construction of these Cost variables. We exclude borrowers from 9 loan officers who have not worked long enough with our partner lender to be eligible for a bonus. The regression includes the following variables as controls: Principal : Loan amount given to the borrower; Amount at Risk : the complete pending amount if the borrower has 7 or more days late (and zero otherwise); Borrower Loan Cycle : the number of cycles that the borrower has been with our partner lender. Even columns also contain controls for average days late before Baseline, and demographic and business characteristics from Table A1. **Outcome variable**: Columns (1)-(4) report results on an indicator variable that equals 1 for being endorsed at a given round, and 0 if never endorsed. Borrowers who are endorsed in other rounds are excluded from the regressions. So borrowers endorsed at Mitigation or Recognition are excluded from Panel A. Borrowers endorsed at Baseline or Recognition are excluded from Panel B. Borrowers endorsed at Baseline or Mitigation are excluded from Panel C. Borrowers endorsed at Baseline are excluded from Panel D.

Table A9: Repayment Behavior of Groups in Which Someone Graduated

	Late $\geq$ 15 Days	Late $\geq$ 90 Days	Defaulted	Amount Defaulted
	(1)	(2)	(3)	(4)
Panel A: Everyone				
β_{All}: Post	0.007	0.000	0.003	0.845
	(0.005)	(0.001)	(0.006)	(2.996)
Mean: Pre-period	0.002	0.000	0.004	1.556
	[0.042]	[0.000]	[0.065]	[28.257]
Number of Borrowers	2094	2094	2094	2094
Observations	121342	121342	121342	121342
Panel B: Never Endorsed				
β_N: Post	0.007	-0.000	0.006	1.521
	(0.007)	(0.001)	(0.007)	(3.968)
Mean: Pre-period	0.002	0.000	0.005	1.669
	[0.045]	[0.000]	[0.069]	[29.022]
Number of Borrowers	1516	1516	1516	1516
Observations	87395	87395	87395	87395
Panel C: Endorsed at Baseline				
β_B: Post	0.009	0.001	-0.004	-1.685
	(0.008)	(0.001)	(0.003)	(1.386)
Mean: Pre-period	0.001	0.000	0.003	1.458
	[0.035]	[0.000]	[0.056]	[28.267]
Number of Borrowers	516	516	516	516
Observations	30148	30148	30148	30148
Panel D: Endorsed at Mitigation				
β_M: Post	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Mean: Pre-period	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Number of Borrowers	28	28	28	28
Observations	1667	1667	1667	1667
Panel E: Endorsed at Recognition				
$\beta_{Recognition}$: Post	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Mean: Pre-period	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Number of Borrowers	34	34	34	34
Observations	2132	2132	2132	2132

Notes: **Specification**: This table implements Specification 9. 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 main explanatory variable Post is a dummy variable that equals 1 for periods when the graduating borrower has graduated and left the group, and zero when the borrower is still a member of the JL group. Panel A includes all group members that were in the JL group when the graduating borrower left, whereas Panels B to E include group members that were in the JL group when the graduating borrower left, but restrict the group sample according to the endorsement round of the graduating borrower. Finally, note that the zeros in Panels D and E (variable drops) are caused by no one defaulting in those samples. **Outcome variable**: Column (1) reports results on a dummy variable that equals 1 if the borrower is 15 or more days late in their installments, and zero otherwise; Column (2) reports results on a dummy variable that equals 1 if the borrower is 90 or more days late in their installments, and zero otherwise; Column (3) reports results on a dummy variable that equals 1 if the borrower defaulted, and zero when the borrower has not defaulted yet; and Column (4) reports results on a continuous variable containing the amount defaulted by a borrower if the borrower defaulted, and equals zero when the borrower has not defaulted yet.

E Formula for Computing Loan Officer Compensation in Section 5

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

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

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

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.

Instruments for Section 5

In interviews with loan officers, it became apparent that by far the most salient threshold were those based on the number of borrowers (i.e. those that determine Range), and the 3% threshold for portfolio at risk, which determines whether loan officers have access to a bonus at all. Therefore the instruments we construct for our regressions in Section 5 are based on the distance between a loan officer's portfolio and these thresholds.

Namely these are:

- $Dist_{169} \equiv 169 - n$ if $n < 169$ where n is the number of borrowers a loan officer manages. $Dist_{169}$ takes a filler value if $n \geq 169$ as this distance is no longer relevant, and a dummy is included indicating if the filler value is used.
- ${Dist_{169}}^2$
- $Dist_{351-} \equiv 351 - n$ if $n \in [169, 350]$. $Dist_{351-}$ takes a filler value if $n < 169$ or $n \geq 351$, and a dummy is included indicating if the filler value is used.
- ${Dist_{351-}}^2$

- $Dist_{351+} \equiv n - 351$ if $n \geq 351$. $Dist_{351+}$ takes a filler value if $n < 351$, and a dummy is included indicating if the filler value is used.
- ${Dist_{351+}}^2$
- $Dist_{3\%-} \equiv 3 - r$ if $r \leq 3$ where r is the loan officer's portfolio at risk. $Dist_{3\%-}$ takes a filler value if $r > 3$, and a dummy is included indicating if the filler value is used.
- ${Dist_{3\%-}}^2$
- $Dist_{3\%+} \equiv r - 3$ if $r > 3$ where r is the loan officer's portfolio at risk. $Dist_{3\%+}$ takes a filler value if $r \leq 3$, and a dummy is included indicating if the filler value is used.
- ${Dist_{3\%+}}^2$

We utilize separate instruments for loan officers above and below 351 borrowers and above and below 3% at risk as there is an asymmetric effect of crossing these thresholds from above and below.