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Abstract

In many firms, incentivized salespeople with private information about their customers are responsible for customer relationship management (CRM). Private information can help the firm by increasing sales efficiency, but it can also hurt the firm if salespeople use it to maximize own compensation at the expense of the firm. Specifically, we consider two negative outcomes due to private information —ex-ante customer adverse selection at the time of acquisition and ex-post customer moral hazard after acquisition. This paper investigates potential positive and negative responses of a salesforce to managerial levers--multidimensional incentives for acquisition and retention performance and job transfers that affect the level of private information.

Salespeople are responsible for managing customer relationships and compensated through multidimensional performance incentives for customer acquisition and maintenance at many firms. This paper investigates how a salesperson's private information on customers affect their response to multiple dimensions of incentives. Using unique matched panel data that links individual salesperson performance metrics with customer level loans and repayments from a microfinance bank, we find that sales people indeed possess private information that is not available to the firm. Salespeople use the private information to engage in adverse selection of customers in response to acquisition incentives. Customer maintenance incentives serve a dual purpose; they not only reduce loan defaults, but also moderate adverse selection in customer acquisition. Transfers that eliminate private information reduces the adverse selection effects of acquisition incentives, but increase loan defaults—customer moral hazard. Despite the potential negative adverse selection effects due to private information, the effort increasing effect of each of the three dimensions of sales management we investigate---acquisition incentive, maintenance incentive and transfers all have a net positive effect on firm value. Methodologically, the paper introduces an identification strategy to separate customer adverse selection and customer moral hazard (loan repayment), by leveraging the multidimensional incentives of an intermediary (salesperson) responsible for both customer selection and repayment with private information about customers.

1 Introduction

Firms increasingly recognize the value of customer relationship management (CRM). CRM recognizes that although acquiring customers is important, maintaining customer relationships—and ongoing revenue streams--is even more critical for profitability (Jain and Singh 2002, Li, Sun and Montgomery 2011, Shin and Sudhir 2010, Reinartz, Krafft and Hoyer 2004, Venkatesan and Kumar 2004). In many B2C markets, salaried marketers are responsible for the CRM functions of acquiring customers and maintaining customer revenues using a centralized customer database; the academic marketing literature on customer management has generally focused on such settings (Gupta and Lehmann 2005, Venkatesan and Kumar 2004). But in many B2B markets and even B2C markets such as financial services in which high customer-level profit margins support ongoing personal selling, incentive-driven salespeople develop and manage customer relationships.[1]

When using incentive-driven salespeople for customer management in B2B markets, two issues arise that have received little attention in the B2C literature on CRM. First, the extant literature on sales incentives is typically based on unidimensional measures of performance, typically sales revenues (e.g., Chung, Steenburgh and Sudhir 2014; Misra and Nair 2011). But such single dimensional compensation plans are inadequate for CRM as they do not decompose performance in terms of sales generated from newly acquired customers and profit generated through maintaining relationships with existing customers. Hence incentives are tied to multidimensional—acquisition and maintenance—performance of the sales person. Second, salespeople can have private information on customers through their relationships with customers. Private information can increase a salesperson's efficiency and thus help the firm, but it can also hurt the firm if salespeople use it to maximize own compensation at the expense of the firm. Specifically, we consider two negative effects due to private information that can negate the productivity enhancing effects of incentives: ex-ante customer adverse selection at the time of acquisition and ex-post customer moral hazard after acquisition.

[1] Interestingly, the best-selling CRM software is salesforce.com, which started as sales automation software and primarily serves as a tool for salespeople to manage customer relationships.

This paper investigates how salespeople responsible for customer management respond to multidimensional performance incentives relevant for CRM, in the presence of private information about customers. Specifically, we study the salespeople's response to three levers that impact incentives and private information and commonly used to manage a salesforce responsible for CRM: (1) acquisition incentives (2) maintenance incentives and (3) job transfers that affect the level of private information.

We outline the managerial tradeoffs involved in the use of these levers. While acquisition incentives enhance productivity by motivating salespeople to bring in more customers, in the presence of private information, it may motivate salespeople to selectively target easier-to-acquire, poorer-quality customers with lower lifetime value (adverse selection).[2] Maintenance incentives can not only improve customer maintenance and reduce customer moral hazard ex-post, but also incentivizes forward looking sales people to ex-ante not acquire lower quality customers (mitigate adverse selection). This is because maintenance incentives give salespeople a stake in the future cash flows from customer; making them consider the potentially negative consequences for their own future incentives from acquiring lower quality customers. Periodic job relocation or rotation can reduce the potentially negative effect of private information by eliminating private information.[3] But relocation eliminates not only the negative adverse selection effects of private information but also the efficiency enhancing effects. Whether salesperson relocation is profitable for the company is therefore an empirical question.[4]

[2] The issue of adverse selection in response to sales incentives has received much attention in the popular press in the context of the subprime mortgage crisis. Loan officers in banks were accused of approving mortgages to customers with less than stellar credit, by disguising their lack of credit worthiness in formal applications in order to receive loan acquisition bonuses (reference and/or quote) as they were not responsible for subsequent performance. The issue of adverse selection is also critical in other marketing settings where firms invest substantially in customer acquisition and hope to recover the benefits of their investments over the life of the relationship. If salesperson knowingly acquire customers who are likely to stop doing business relatively soon after being acquired and before the acquisition costs have been recouped, such acquisitions can destroy firm value, rather than adding to firm value.

[3] Transferring employees is a common practice in the banking and B2B finance sector. For example, France, Germany, Italy and the United States, for example, mandate rotation of audit partners across clients. Also see discussion in Fisman, Parvasini and Vig (2011) on mandated transfers in the Indian state banking sector.

[4] Firms typically do not have levers either contractually or through incentives to appropriate this asset from the salesperson so that the firm can take advantage of the efficiency enhancing effects and avoiding the adverse selection

Given the background of the tradeoffs involved, the papers addresses the following research questions: (1) is there evidence of private information among salespeople? (2) do acquisition incentives lead to adverse selection? (3) do maintenance incentives mitigate adverse selection? (4) do transfers mitigate customer adverse selection, but increase moral hazard? (5) do the acquisition/maintenance incentives and transfers overall have a net positive or negative effect on firm profitability?

Answering these questions pose a number of challenges. First, one needs matched panel data on sales force incentives/performance and customer relationships over time. This is typically difficult to obtain, as such data tend to reside separately within different functions of a firm. Specifically, the sales incentive and performance data reside within human resource/sales functions within a firm, whereas detailed customer panel data reside within the marketing function. We were fortunate to work with a microfinance bank in Mexico that lends to small business customers and was willing to match the panel data on performance/compensation/transfer information about their loan officers (salespeople) with the loan acquisition and repayment behavior of their customers.

Second, detecting evidence of private information is typically challenging due to its intrinsic unobservability. Our primary identification strategy leverages the idea that salesforce performance and incentives should not directly affect consumer repayment behavior but only indirectly through salespeople's efforts. Specifically, correlation between compensation performance and borrower repayment behavior conditional on credit rating, loan characteristics and various unobserved demand shifters is driven by private information held by salespeople about customers. In other words, if there is no private information for salespeople beyond what the company knows, then there should be no systematic relationship between salespeople's incentive state and repayment behavior because a salesperson compensation status is not observable to borrowers.

Finally, beyond the unobservability of private information, it is generally not feasible to observe exogenous changes in private information. In our empirical setting, the microfinance bank randomly

effects. For instance, although firms encourage salespeople to input information about the status of their ongoing conversations with prospects and stage of conversion in CRM tools such as salesforce.com, salespeople are reluctant to part with this information, which they view as their own assets for which they receive no rewards for sharing with the firm.

transferred their salespeople—the loan officers. The bank chose a randomized transfer strategy when loan officers cannot predict the likelihood of their transfers so that loan officers may not indulge in relationship harvesting bad behavior as the likelihood of transfer increases, because they will not be as responsible for the consequences of the bad behavior. Thus in our setting transfers serve as an exogenous instrument for how changes in private information affect responses to incentives.

Our key findings are as follows: Overall, we demonstrate that private information is a relevant issue — salespeople indeed possess private information about customers not available to the firm. In response to customer acquisition incentives, salespeople indeed "abuse" the private information to engage in adverse customer selection—acquiring customers that controlling for observables known to the firm have lower expected profits. Customer maintenance incentives serve a dual positive purpose for the firm; they not only reduce ex-post loan defaults (customer moral hazard), but also moderate ex-ante adverse selection in customer acquisition. Private information has both positive and negative effects. When firms eliminate private information through job location transfers, it reduces adverse selection in response to acquisition incentives, but also increases loan defaults (customer moral hazard). But overall, the net effect of transfers is positive. Importantly, without the pressure of maintenance incentives, the positive effect of customer acquisition incentives will be neutralized by the negative effect of adverse selection through reduced customer quality at the margin.

The paper contributes to multiple literatures in marketing and economics. Substantively, the paper extends the literature on CRM and sales force compensation. First it extends the CRM literature (e.g., Venkatesan and Kumar 2004), which has abstracted away from the role of an incentivized sales force to obtain desired customer management outcomes—an issue that is particularly important in B2B settings. In particular, the paper highlights the challenge of private information among salespeople in incentivizing the salesforce as it can have both positive and negative effects.

Second, it expands the empirical literature on sales force compensation to move beyond a unidimensional performance measure (e.g., Misra and Nair 2011; Chung, Steenburgh and Sudhir 2014) to consider multidimensional performance benchmarks and address the multi-tasking agency problem highlighted by Holmstrom and Milgrom (1991) so that the salesforce balance their efforts across multiple dimensions. The issue of course is critical in B2B CRM settings. In our particular application, this balance is not just in allocating effort on two contemporaneous performance dimensions, but in addressing the right balance between short-run and long-run performance. In so doing, it addresses the challenges associated with limited liability of agents (e.g., Sappington 1983, Oyer 2000, Simester and Zhang 2014). Holmstrom and Milgrom (1994) leading to a focus on short-run performance by combining "short-run" acquisition incentives with "longer-run" maintenance incentives. Customer maintenance incentives are a way of providing an ongoing stake in the "customer asset" for the salesperson and a means of aligning incentives between salespeople and the firm through an effective "partial ownership" (Grossman and Hart 1983).

Methodologically, this study contributes to a growing literature that empirically tests for the existence of private information and distinguishes the effects of customer adverse selection and moral hazard in insurance and credit markets. Identifying the existence of private information and quantifying its effect are challenging because of its intrinsic unobservability. Previous studies address this problem by obtaining access to additional information unused by a firm (Finkelstein and McGarry 2006, Finkelstein and Poterba 2004). Moreover, by only observing customer behaviors ex post, researchers cannot disentangle the source from adverse selection ex ante and moral hazard of them ex post.[5] Past studies address the issue through a randomized controlled experiment with contract terms (Karlan and Zinman 2009) or by exploiting policy changes (Dobbie and Skiba 2013). We introduce a new identification strategy that exploits "supply-side" variation in the salespeople's motivation to use private information at the point of customer acquisition and maintenance and a policy that explicitly changes the level of private information about customers to separate customer adverse selection and customer moral hazard.

[5] A positive correlation test proposed in Chiappori and Salanie (2000) explores the evidence of asymmetric information but does not separate adverse selection and moral hazard. For example, even when an insurance company finds a positive correlation between the plan coverage and the number of claims, it cannot fully attribute this finding to adverse selection (i.e., high-risk consumers opt into generous plans) or moral hazard (i.e., those who enroll in generous plans tend to become involved in risky actions).

The rest of the paper is organized as follows. Section 2 introduces institutional details and the data. Section 3 explains our empirical strategy and results and discusses the key findings. Section 4 assesses the robustness of the key results. We conclude and provide future research direction in Section 5.

2 Institutional Details and Data

We begin with a description of the institutional details of our empirical setting and describe the data used in our empirical analysis.

2.1 Institutional Details

Our empirical application is in the context of a Microfinance Institution (MFI) in Mexico that lends to low income, small business entrepreneurs through loan officers (salespeople) without collateral. The loans offered are typically small (median of $690), high interest rate (median rate is 85%), short maturity (median length is 6 months) and high delinquency probability (average of about 25.4%), as is common for microcredit in emerging markets.[6]

The loan officers have two main responsibilities: acquiring new loans and ensuring repayments on existing loans. The acquisition stage involves recruiting borrowers through referrals and database searches, accepting loan applications and recommending loan terms to the bank. Banks use public information about the borrower available to the bank and information in the loan application to generate a five point credit rating for each borrower. This is used to both approve the loan and set the interest rate. Given acquisition, officers ensure that loans are repaid on time (e.g., through phone calls and in-person visits). During this process, loan officers can obtain private information about clients' motives, financial capabilities/liabilities and build relational capital. Our interest lies in how loan officers use this private information to enhance their incomes—either

[6] See, e.g., Sengupta and Aubuchon (2008) for more discussion on microcredit loans in emerging markets.

through increased efficiency in customer acquisition and maintenance that are also beneficial to the firm or through adverse customer selection, which hurts the firm.[7]

The firm offers a salary and a bonus that is a multidimensional function of both acquisition and customer maintenance performance. Acquisition performance is benchmarked against one's own past performance to create an index of performance (A_{jt} for officer j at period t). The maintenance performance index is based on the number and value of loans collected relative to the loans outstanding (M_{jt}). The salespeople's bonus is the product of the acquisition index, maintenance index and their base salary (i.e., $Bonus_{jt} = Salary_{jt} * A_{jt} * M_{jt}$); thus, receiving zero points in any category would earn them no bonus at all. Note that the multiplicative feature of the incentive scheme leads officers to balance effort between acquisition and maintenance in any given time period. Further, the multi-dimensionality of the compensation plan introduces a dynamic trade-off for the salesperson: between the immediate benefits of acquiring lower quality customers to improve acquisition performance, and its future negative effect on maintenance performance.

Finally, the bank periodically relocates loan officers from their current branch to another branch.[8] A particularly interesting characteristic of the transfer policy at the MFI is that the transfers both in terms of timing and location are entirely random. The randomness in timing is intended to prevent loan officers from engaging in greater adverse selection, when their expectations of transfer are high. We check that the transfer policy is indeed random and exogenous with respect to officers' characteristic, previous performances and geographical region, as conceived by the firm. Fortunately, for our econometric analysis, this means we can treat transfers as an exogenous shock to salesperson private information and do not need to account for endogeneity concerns.

2.2 Data

[7] Although our data allow us to study repayment behavior within a loan, we lack sufficiently long panel data to study customer maintenance and repayment behavior across loans. In this paper, we treat repayment within the loan as corresponding to maintenance.

[8] Such transfers are common in the banking sector to avoid potential abuse of the private information by loan officers to avoid adverse selection. (Hertzberg, Liberti and Paravisini 2010, Fisman, Paravisini and Vig 2011).

Our panel data include monthly salesforce performance and compensation data matched with the transactions on loans generated and maintained by the salesperson. We observe 461 loan officers working on 129,839 loans for 14 months from January 2009 to February 2010. The loan data include information on loan characteristics such as the borrower's credit rating, loan terms (e.g., amount, interest, origination date and loan duration) and details of loan repayment (e.g., monthly payments, delinquency). The loans are also matched with the loan officer who generated the sale, and the loan officer currently maintaining the loan (which is typically the originating officer, except when there is a transfer). For each loan officer, we have monthly information on the points on the acquisition and maintenance benchmarks, based on which the bonus is computed.

We report summary statistics of loan characteristics and bonus points in Table 1. The average loan size is 9,192 pesos (approximately 690 US$ in 2009), with an average loan term of 6 months. The average interest rate as is typical in many emerging market for loans without collateral is high at 87%. The high interest rate reflects both a high overall delinquency rate of approximately 25.4% and the very high cost of acquiring and collecting loans.[9] The average of monthly acquisition points (A) is 0.75 and maintenance points (M) is 0.85 across the salesforce and across time; and the average of the overall bonus multiplier (A*M) is 0.59 of the salary.[10] More details on the marginal distributions of loan characteristics and points are presented in the Appendix.

Next, we report on the relationship between bank's credit rating of borrowers and loan performance. The bank's rating of borrowers is shared with the loan officers who sell the loan and the loan underwriters, who approve the terms of the loan. Figure 1 shows that the delinquency probability falls and Internal Rate of Return (IRR) of a loan[11] improves as the credit rating goes up indicating that the credit rating is a reliable predictor of borrower quality and the loan's risk

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[9] Approximately 56% of the loans are not repaid on time at least once.

[10] We observe officers' base salary only in the last period for 273 officers. They earn 4050 Mexican pesos (313 USD) as base salary on average, with a standard deviation of 1650 pesos. Base salaries are determined by seniority, not by performance.

[11] We compute IRR of each loan based on loan size and returned amount over time. Our data do not include exact cash inflow; thus, we make the following assumption on the returned amount: a borrower decides to make zero repayment in the delinquent period and make full repayment in other periods. A loan officer cannot collect any amount from the period in which the loan defaults.

and performance. Table 2 further explores the relationship between credit rating and loan characteristics. 71% of the loans are given to those with credit ratings of 5, 18% to those with credit ratings of 4. Only 11% of loans are given to those with credit ratings of 3 and below. The interest rates are roughly the same across credit ratings, though the standard deviations are high. i.e., the bank does not seem to increase the interest rate to compensate for its greater risk. Instead, duration of the loan is greater for those with lower credit ratings, this may be the bank's attempt to make it feasible for borrowers with lower incomes to help pay back the loan.

Figure 2 shows that 33.4% of officers went through a transfer, and 3.2% did so more than once during the observation window. We check that the transfer policy is indeed random and exogenous as conceived by the firm. Table 3 reports the results of a logistic regression with transfer as a dependent variable, and observable officer characteristics as explanatory variables. Transfer is not related to any of the officers' characteristics, such as tenure, the number of months since their previous transfer, gender, or previous period performance, confirming the firm's description of the implementation of the transfer policy.[12]

[Insert Table 1, Figure 1, Table 2, Table 3]

3 Empirical Analysis

We begin with a discussion of our identification strategy and then outline the steps of our empirical analysis to answer the research questions we raise in the paper.

3.1 Identification Strategy

Given that a salesperson's private information is inherently unobservable, it is challenging to demonstrate the presence of private information, and identify the effects of such private information on salespeople's performance outcomes. As we allude to in the introduction, there are two key ideas in our identification strategy to detect salesperson private information, customer adverse selection

[12] We also find that the transfer decision is not correlated with officers' past performances up to 3 months before transfers, or other officer characteristics, such as education level, marital status, relationship type (Canales and Greenberg 2015) or position in the firm.

and customer moral hazard. The first is that a salesperson's motivation to use the private information, if available, to achieve acquisition and retention performance benchmarks varies over time as a function of observable to researchers "states" of the salesperson. If the loans offered by a salesperson during periods their motivation to engage in adverse selection is greatest perform worse (controlling for observables available to both salesperson and the firm), we treat that as evidence for both sales person private information and customer adverse selection. Similarly, if the probability of repayment (customer moral hazard) changes as a function of the pressure to achieve maintenance benchmarks (after controlling for observables), that is evidence of salesperson private information and customer moral hazard. The key identification assumption is that the sales person incentive states and motivations are orthogonal to customer and loan characteristics because customers do not observe officer incentive states.

Second, the random transfer policy of the MFI provides us another exogenous "supply" variation in the level of private information among salespeople on their customers. By relocating loan officers to new branches and forcing them to acquire and maintain new customers, the MFI renders the salespeople's private information from established customer relationships useless for performance. Comparing the continuing officers' customer acquisition and retention performance outcomes against transferred officers' performance outcomes helps us identify the effect of private information on customer adverse selection and moral hazard. Again, the key identification assumption is that the transfer policy creates a supply-side variation that is not correlated with demand-side factors, such as customer and loan characteristics.

3.2 Empirical Strategy

Our empirical analysis proceeds in three steps. First, we examine selection effects on the quality of loans originated due to acquisition incentives, retention incentives and job rotation. This allows us to test for both the existence of private information and how the three managerial levers impact adverse selection. Second, we examine ex-post consumer moral hazard after loan origination i.e., repayment/delinquency behavior in response to the three levers. Finally, we examine the overall effects of the three levers on firm profitability; i.e., we test whether the effort e.

3.2.1 Ex-Ante Selection Effects when Originating Loans

We begin with a test for whether the performance of a loan is a function of the acquisition, maintenance and transfer states of the officer at the time of origination of the loan by estimating the following empirical model.

$$IRR_{ijo} = \beta_0 + \beta_1 \widetilde{A}_{jo} + \beta_2 \widetilde{M}_{j,o-1} + \gamma_1 Transfer_{jo} + \gamma_2 X_i + \mu_j + \varphi_o + \varepsilon_{ijo} \qquad (1)$$

In equation (1), we measure loan performance through IRR_{ijo}, the internal rate of return of loan *i*, originated by officer *j* at time *o*. The variables representing incentive states are Acquisition index at $o, \widetilde{A}_{jo}$, the Maintenance index at *o-1*, denoted by $\widetilde{M}_{j,o-1}$.[13] The dummy variable $Transfer_{jo}$ equals 1 if officer *j* was new to the branch at origination period. The model also controls for observable loan characteristics in X_i, such as borrower's credit rating, loan amount, duration, interest rate and the number of months since origination. Furthermore, the model includes loan officer fixed effects and time fixed effects to capture any unobserved heterogeneity of loan officers and market shocks such as competition against other banks or macroeconomic financial shock.[14]

The coefficients we are primarily interested in are β_1, β_2 and γ_1. The coefficients β_1 and β_2 in equation (1) represent how IRR of each loan changes in response to sales force incentives at acquisition period *o*, conditional on observables and salesperson/period fixed effects. Controlling for observables, salespeople can use their private information to go after "easier to acquire" loans with lower IRR. Negative β_1 implies that as the salesperson's performance on the acquisition increases in the period, IRR of the loans fall, indicating adverse selection. Negative β_2 implies that adverse

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[13] We construct demeaned variables $\widetilde{A}_{jo}$ and $\widetilde{M}_{j,o-1}$ to eliminate any effect of cross-sectional unobservables. The demeaned variables measure how well or badly each officer performs, relative to her own average performance. The demeaned Acquisition points are computed as $\widetilde{A}_{jo} = A_{jo} - \frac{1}{N_j}\sum_{k=1}^{N_j} A_{jk}$, where N_j is the number of periods that officer *j* appears during the observation window. While acquisition points are considered for time period *o*, based on the acquisition at period *o*, which is controlled by the loan officer. For maintenance, we consider the index from *o*-1, which indicates the level of pressure for ensuring repayment in period o. However, the actual maintenance index in period 0 is not realized until after the end of the period, and is not entirely under the loan officer's control.

[14] In this specification, we abstract away from potential concerns of endogeneity of loan terms *X*, but will revisit the robustness of our conclusions to potential endogeneity of loan terms in Section 4.

selection is moderated by the maintenance incentive and that officers are forward-looking, i.e., officers under high maintenance pressure (i.e., those who showed poor maintenance performances at *o-1*) screen out unprofitable borrowers at o to prevent higher delinquency risk in the future (which would further worsen their maintenance metric) and therefore acquire higher IRR loans, controlling for observables. The coefficient γ_1 shows the effect of the transfer policy. A positive γ_1 shows that transferred officers acquire better loans than do continuing officers, suggesting that salespeople with little private information (relational capital) are likely to engage less in adverse selection.

Table 4 reports the results. In Model 1, a one-point increase in acquisition performance relative to the loan officer's average leads to 0.54% decrease in IRR of new loans. A one-point decrease in the previous period's retention performance, which generates motivation to earn retention points, leads to a 1.07% increase in IRR of new loans. Transferred officers, whose private information is eliminated, bring in higher-quality loans at 2% of IRR. This shows evidence of private information among the salesforce, that higher acquisition performance accentuates adverse selection, and maintenance pressure mitigates adverse selection and transfers mitgate adverse selection.[15]

Model 2 adds the interaction term between two incentive components, and Model 3 includes quadratic terms of demeaned incentives to capture potential nonlinearities. The results above remain robust; all of the specifications support the hypothesis that the marginal quality of the loan suffers due to the loan officers' use of private information to accept risky borrowers.

Coefficients of other variables exhibit the expected direction. As observable credit rating increases, IRR goes up. Smaller loan, longer duration and higher interest rate are associated with lower profitability.

[Insert Table 4]

3.2.2 Ex-post Customer Moral Hazard

Next, we investigate how the acquisition/maintenance incentives and transfers impact customer moral hazard, i.e., repayment behavior or delinquency. Given private information, loan

[15] The results remain consistent when we measure loan performance through 1) the number of late repayments, 2) the probability of late repayments and 3) the failure to collect a loan on time at least twice during the loan cycle.

officers can increase monitoring to reduce customer's moral hazard on repayment especially when they are under high maintenance pressure. However, transferred officers without private information may perform worse on this dimension as they have less information on where to focus their monitoring effort. As there is a balance between time spent on acquisition and maintenance, higher customer acquisition may be related to greater delinquency.

$$\begin{aligned} Delinquency_{ijt} = {} & \beta_0 + \beta_1 \tilde{A}_{jt} + \beta_2 \tilde{M}_{j,t-1} + \gamma_1 Transfer_{jt} \\ & + Bad_{i,t-1}(\beta_3 + \beta_4 \tilde{A}_{jt} + \beta_5 \tilde{M}_{j,t-1} + \gamma_2 Transfer_{jt}) + \gamma_3 X_{it} + \mu_j + \varphi_t + \varepsilon_{ijt} \end{aligned} \tag{3}$$

In equation (3), $Delinquency_{ijt}$ is the dummy for delinquency of loan i at time t belonging to officer j. The model separately examines the effects on loans that are already delinquent at the end of t-1, which is represented by the indicator.[16] We believe sales people will have greater impact on loans that are not already delinquent, and therefore sales incentives will have greater impact on such loans. The model also controls for loan characteristics and officer and period fixed effects.

The main coefficients of interest are coefficients concerning maintenance points, which primarily incentivizes ensuring repayments on loans. A positive β_2 shows that salespeople under high maintenance pressure (i.e., low $\tilde{M}_{j,t-1}$) increase monitoring intensity to improve borrowers' repayment behavior at t. A positive γ_1 indicates the removal of private information due to transfer at t causes increases delinquencies; suggesting that private information and the relational capital with the borrowers does help in ensuring repayment and that they are able to target the efforts on the right borrowers. We expect β_5 to be negative as loan officers are likely to be less effective on getting repayments of already bad loans relative to loans in good standing, even with maintenance incentives.

The estimates are reported in Table 6. Model 1 has only retention incentives as the incentive pressure at t, Model 2 has both acquisition and retention incentives, Model 3 adds the interaction of the two components, and Models 4 and 5 do not differentiate between high-quality and low-

[16] We check the robustness of results with other definitions of the variable (e.g., delinquency for 2 or 3 consecutive periods, delinquency for more than 10% of time up to period *t-1*).

quality loans. The coefficient of $\widetilde{R}_{j,t-1}$ is positive and significant in Models 1, 2 and 3, indicating that retention pressure improves monitoring and reduces delay of good loans. Specifically, a one-unit increase in retention points in period *t-1* (which decreases retention pressure in period *t*), leads to a 2% increase in the delinquency probability of loans in period *t* among loans in good standing at *t-1*. Across Models 1-3, the coefficient of $Transfer_{jt}$ is consistently positive and significant, indicating that that the elimination of private information about customers from salespeople through transfers hurts loan repayment by 0.4%. Interestingly acquisition effort and maintenance effort are not substitutes; the negative coefficient of $\widetilde{AG}_{jt}$ in Model 2 indicates that acquisition and retention performance are complementary. Officers expanding their acquisition effort for new loans also have better maintenance performance. This is of course due to multiplicative nature of the acquisition and repayments performance on incentives.

A large effect of $Bad_{i,t-1}$ suggests that loans that are already delinquent are more likely to remain so. Thus, under high retention pressure, officers are less likely to monitor such low-quality loans and more likely to focus on the loans in good standing. The negative coefficient of $Bad_{i,t-1} * \widetilde{R}_{j,t-1}$ suggests that low-quality loans receive less monitoring and ultimately become delinquent under high retention pressure. Transfer has little effect on bad loans, because continuing salespeople do not exert sufficient efforts to maintain the borrowers.

[Insert Table 5]

3.2.3 Total Profits of Loans Generated by Salesperson

Next we test whether the net effect of the acquisition, maintenance and transfer levers is positive or negative across loans generated by a salesperson over the month. This allows us to test whether the sales-enhancing effect of the managerial levers of incentives demonstrated in the existing literature (e.g., Chung, Steenburgh and Sudhir 2014) and transfers exceeds the the negative adverse selection effect due to the private information on marginal loans. To investigate the question, our analysis is now salespeople-month level rather than at the loan-level. In particular, we run the following model in equation (2), where we test whether the total NPV of the loans generated by salesperson j at period o is positively or negatively affected by the three levers.

$$\overline{\overline{NPV}}_{jo} = \beta_0 + \beta_1 \widetilde{A}_{jo} + \beta_2 \widetilde{M}_{j,o-1} + \beta_3 (\widetilde{A}_{jo} * \widetilde{M}_{j,o-1}) + \gamma_1 Transfer_{jo} + \mu_j + \varphi_o + \varepsilon_{jo} \qquad (2)$$

The dependent variable $\overline{\overline{NPV}}_{jo}$ represents the sum of the net present value of new loans acquired by officer j at period o. The coefficients β_1, β_2 and β_3 show the effect of incentive components on the overall quality of loans originated by officer j. The coefficient γ_1 shows the effect of the transfer decision at the point of origination on profits generated by salesperson j.

Table 5 reports the regression results. Model 1 is the baseline case and the estimates show $\beta_1 > 0$, $\beta_2 > 0$, and $\gamma_1 > 0$ and the effects are statistically significant. This shows that each of the levers considered contribute positively to firm profits. However we need to consider the interaction between acquisition and maintenance states to understand how these incentives jointly affect profitability. Model 2 adds the interaction term between acquisition points and retention states, and Model 3 adds squared terms of the incentive states to capture potential nonlinearities.

We represent the interaction effects estimated in Model 2 in Figure 3. When the salesperson is under high maintenance pressure (i.e., those whose previous-period maintenance points are 0.5 point below their average points), greater acquisition performance leads to a sharp increase in profits, but when the maintenance pressure is low (0.5 point above their average points), an increase in acquisition points lead to very little increase in profits. Thus in the absence of maintenance pressure, salespeople engage in significant adverse selection which effectively neutralizes all the profits from customer acquisition. In effect, the firm is paying out commissions with little gains in profitability. This shows that without the use of maintenance metrics of performance that penalizes for ex-post delinquency, salespeople will resort to significant adverse selection that destroys firm profitability.

[Insert Table 6 and Figure 2]

3.3 Managerial Implications

Our findings have large managerial implications concerning salesforce management. First, our results imply that delegating the CRM function to sales agents and implementing performance-based incentives can be complementary, as theoretically shown by Holmstrom and Milgrom (1994). We find that delegating CRM functions to sales agents can be more profitable when they effectively utilize accumulated relational capital (i.e., private information). A carefully designed performance-based incentive scheme prevents sales agents from taking advantage of the information to shirk, and the company can benefit from the relational capital. In other words, our results indicate that a performance-based incentive scheme can enhance the benefits of relational capital.

Second, related to the first point, multi-dimensional incentive plans, which reward both customer acquisition and retention, are useful to utilize relational capital effectively when sales agents directly manage the customer relationship. The traditional *unidimensional* incentive plan, as studied in the existing papers, does not effectively motivate salespeople to value the long-term profit that each customer generates. In contrast, splitting acquisition bonus and retention bonus forces sales agents to consider not only short-term profits but also long-term profits. We demonstrate that sales (acquisition) incentive can increase performance but intensify customer adverse selection, and that retention incentive alleviates customer adverse selection because salespeople now consider the effect of their current acquisition behavior on future retention performance. Hence, our work sheds new light on the role of multi-dimensional compensation plans in CRM.

Third, our findings also suggest what managers must consider when considering job rotation. We find that random job transfers can be used to avoid undesirable consequences of relational capital. Because relational capital is owned by salespeople and not transferrable across them, the firm completely shuts off unobserved or unreported information about a customer upon sales agent rotation. Transferred salespeople, with less private information than continuing ones, are less likely to participate in adverse selection and more likely to mismanage existing customers' moral hazard. Transfers have a positive net effect on overall productivity in our setting, but the effects would be heterogeneous across industries depending upon how salespeople use their private information. Overall, our results provide useful guidance for managers in designing salesforce management systems, particularly when sales agents are in charge of CRM.

4 Robustness Checks

We complement our main results with robustness checks. First, we consider whether potential endogeneity issues in loan terms change our results concerning loan officer private information by an instrumental variable approach. Second, we perform a falsification test of our main hypothesis by considering continuing and transferred officers separately. Finally, we examine whether unobserved branch-level local unobserved heterogeneity drives our results. Other robustness checks we perform can be found in the Appendix.

4.1 Endogeneity in Loan Terms

In Section 3.2, one might be concerned with endogeneity issues of loan terms because they are determined by both sales agents and borrowers through negotiation. Salespeople, however, consider expected profitability of loans when deciding loan characteristics, which can lead to endogeneity in loan terms. In this robustness check, we assess by calculating the models with instruments for loan amount and duration.

Our instrumental variable is the average loan characteristics of other loans acquired by the same loan officer j at period o.[17] The variables affect loan characteristics of loan i, because loan size, for example, reflects loan officer j's overall tendency to approve large or small loans. Loan size is also a function of negotiation between the officer and the borrower; thus, it provides a variation not fully captured by officer fixed effects or officer's incentive points. However, the average characteristics of other loans should not directly affect the *ex post* profitability of loan i.

We report the results in Table 7. With instrumenting, IRR is now negatively correlated with loan amount and positively with duration in Model 1. The reversed sign of coefficients verifies endogeneity in loan terms.[18] We find that the effects of our main variables interest, Acquisition point

[17] Our idea of instrumental variables is similar to Berry, Levinsohn and Pakes (1995), in which the authors use the characteristics of other products as instruments to control for endogeneity of price.

[18] Controlling for the selection effect, the negative coefficient of loan amount implies that those who have greater loans are more likely to default, which is a moral hazard, whereas the remaining selection effect is positive, which implies advantageous selection. In contrast, the moral hazard effect of duration is limited. Those loans with longer duration are lower quality, which results in adverse selection in terms of duration.

and Retention point become stronger once the endogeneity issue is addressed. Hence, despite loan terms being subject to endogeneity, our main results are robust.

[Insert Table 7]

4.2 Endogeneity in branches where the officers are transferred

In Section 3, one of our key identification strategies relies on *random* salespeople transfers. Although our findings in Table 3 suggest that the firm's transfer policy is random, officers in under-performing branch are still likely to be transferred to high-performing branches or branches in good market condition. If so, transferred officers may face a more profitable customer base in a new branch; thus, her new loans might perform better, which has nothing to do with effects of private information. To address this concern, we include branch fixed effects and estimate coefficients in equations (1) and (2).

Tables 8a and 8b show that our main results remain consistent with branch fixed effects. We add Model 1 without branch fixed effects from Tables 4 and 5 for comparison. At the acquisition stage described in Table 8a, loan officers still become involved in adverse selection as they expand their acquisition efforts, with a one-unit increase in acquisition state pushing up IRR by 0.4%. The retention pressure forces officers to look forward and hold out for risky loans. The incentive states have smaller effect in Model 2 than in Model 1, since branch-level market conditions (i.e., overall quality of customer base in a branch) is controlled. The coefficient of $Transfer_{jo}$ shows that transferred officers bring in higher quality loans than do continuing officers, even when we focus on within-branch effects. The transfer effect is slightly higher in Model 2, suggesting that the transferred officers bring in higher-quality customers, regardless of branch-level performances. The anticipated performance of a branch or market conditions do not drive transfer decisions.

Table 8b documents salespeople's monitoring behavior within a branch. While the main result remains consistent, the incentive points have smaller effects with branch fixed effects, for both good and bad loans. In Model 2, the effect of transfer represented by the coefficient of $Transfer_{jt}$ is insignificant for good loans, and slightly positive for bad loans, indicating that transferred salespeople do not effectively monitor existing loans, particularly bad loans. Without branch fixed effects in Model 1, transferred officers are not effective in monitoring good loans. We conjecture that this change in findings is due to ( ). The findings indicate that heterogeneity in the customer base across branches does not drive the main results. Salespeople use their private information regardless of the features of the population with which they interact.

[Insert Tables 8a and 8b here]

4.3 Effect of Ratcheting Incentive

We describe that the bank's compensation scheme creates a dynamic consideration for officers, particularly in Acquisition points (A). One may raise a concern that the incentive scheme is not free from ratcheting effect because a loan officer's monthly acquisition goal depends upon previous periods' acquisition performance.[20] While salespeople put acquisition efforts to earn high Acquisition points, they might shirk off to the extent that they fear high sales would only result in an unachievable quota next period.

Although we cannot simulate officers' behaviors under a counterfactual incentive scheme without any ratcheting effect[21] and observed behaviors of salespeople under ratcheting incentives may not maximize their current utility, we believe that the ratcheting effect rather reinforces our adverse selection claims. The ratcheting effect would reduce acquisition efforts; thus, salespeople should engage in less-severe adverse selection. Thus, we argue that our calculations are the lower bound of potential adverse selection of new customers.

Our idea to examine the effect of the ratcheting effect considers that salespeople would not want to exceed the cutoff, above which their quota increases in a discrete manner, even though they

[20] Loan portfolio size at the beginning of each period determines Acquisition Goal and is thus again a function of acquisition performance in past periods.

[21] We leave it for future research. The evidence would demonstrate the advantage of a ratcheting incentive in an organization in which adverse selection is largely detrimental. A ratcheting incentive is commonly considered to hurt a firm because it induces employees to reduce efforts. However, it also causes them to focus not only on sales but also to balance between quantity and quality aspects. Consequently, the firm would benefit from mitigated adverse selection and maintain a high quality customer base.

are able to do so. We separately analyze loans generated by such high-performing officers, whose average Acquisition performance would lead them to exceed the cutoff, and those originated by low-performers. Although officers' average performances, which categorize salespeople into high- and low-performers, are already affected by ratcheting incentives, this analysis would enable us to roughly suggest that ratcheting incentives ameliorate the extent of adverse selection. In Table 9, Model 1 analyzes IRR of loans originated by high performers (i.e., loan officers who would have got higher Acquisition goal if they performed on average) and Model 2 looks into the profitability of loans sold by low performers. We find that high-performers who should be concerned about ratcheting incentives do not show adverse selection behaviors, while low-performers do. The coefficients of $\widetilde{R}_{j,o-1}$ imply that high-performing salespeople are more likely to avoid risky decisions under maintenance pressure. Overall, without ratcheting effect, our main result on adverse selection may have been higher.

[Insert Table 9]

5 Conclusion

In this paper, we empirically study three key issues that arise when incentive-driven salespeople manage customer relationships using the rich micro-level data that include both salesperson compensation/performance data and their customer-level transaction data.

First, when salespeople are delegated CRM, they can obtain private information about customers through interactions with customers beyond what the company can observe from hard information in the customer database. This private information can help salespeople find and maintain good customers, but at the same time the salespeople can also abuse the private information by bringing in bad customers to increase their short-term payoffs.

Second, a unidimensional sales-based incentive scheme, which has been primarily examined in the salesforce compensation literature, might not work well when salespeople are in charge of CRM, whereas a multi-dimensional incentive scheme that rewards both customer acquisition and retention can incentivize salespeople. Thus, we consider how private information about customers influences salespeople's behavior under a multi-dimensional incentive scheme.

Third, the company can exploit temporal job transfers or rotations as a tool to manage the potentially negative effects of private information that salespeople could abuse. Job transfers change salespeople's private information and mitigate the negative effects. Different levels of transfer policies in different industries can reflect the degree of asymmetric information that salespeople can acquire.

Our findings suggest that officers have private information about customers' ability to repay and that they leverage their unobserved knowledge to earn higher incentives. They accept less-deserving borrowers to obtain high acquisition points but become conservative under retention motives because they are afraid that low-quality loans might hurt their future retention points. At the repayment stage, officers become involved in more monitoring to reduce borrowers' moral hazard if they have high retention pressure. Moreover, we find random relocation mitigates adverse customer selection because transferred officers do not have such private information.

Our findings provide important managerial implications for CRM. When managers design a salesforce management scheme, they must consider potential complementarity between delegation of CRM to the salesforce and implementation of a high-powered incentive. Moreover, managers must design incentive schemes carefully so that agents' incentives are aligned with the company to address not only short-term profits but also long-term profits to increase CLV. Finally, job rotation would also influence the effectiveness of an incentive scheme because it eliminates relational capital upon a transfer. Hence, frequency of job rotation should be carefully done together with the design of an incentive scheme and the degree of asymmetric information in the market.

Methodologically, we employ a new strategy to identify adverse selection of customers. Our identification strategy for the effect of private information and adverse customer selection can be generalized to other situations to the extent that customers are not able to observe the supply-side incentives.

This paper does not address how firms that become involved in CRM optimally design salesforce compensation schemes. Structural models of salesforce-driven CRM behavior with multi-dimensional incentive schemes would allow us to answer this question, but we leave it for future research.

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A Appendix

A.1 Details on Compensation Plan

In this section, we provide detailed structure of the compensation policy that the bank implements. Tables A.1 and A.2 exhibit the detailed compensation policy on how Acquisition Goal, and Retention points are determined.

[Insert Table A.1]

The Acquisition Point (A) is the amount of newly acquired loans divided by Acquisition Goal (Table A.1.), which is a function of the loan officer's current total loan amount lent. A loan officer who has acquired many new loans will face a significant increase in his/her Acquisition Goal. Hence, to the extent that he wants to avoid an unachievable high growth point target, the loan officer might not want to increase efforts to acquire new customers. We examine this ratcheting effect in Section 4.

[Insert Table A.2]

As in Table A.2, the retention incentive has non-linear structure. Observe that this non-linear structure does not create any ratcheting incentive for loan officers because current retention points do not mechanically affect future retention points.

Table 1: Summary Statistics

Loan Characteristics		Mean	SD	Min	Max
Amount (pesos)		9,192	8,956	700	55,000
Annual Interest rate (%)		87.21	8.81	42	100.29
Duration (months)		6.27	3.89	1	33
Delinquency (%)		25.42			
Sales Force Incentives and Transfer		**Mean**	**SD**	**Min**	**Max**
By Salesperson-period	Acquisition Point (A)	0.75	0.45	0	3.188
	Maintenance Point (M)	0.85	0.23	0	1.25
By Salesperson	A*M	0.59	0.3		
	No. of Transfers	0.37	0.55	0	3

Table 2: Distribution of Loan Performance and Characteristics across Credit Rating

Credit Rating	N	IRR		Delinquency prob		Interest rate		Duration	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	4,484	45.9	44.57	0.65	0.36	88.67	9.83	10.76	6.38
2	3,089	53.36	39.46	0.59	0.38	86.71	9.58	10.84	6.89
3	6,754	66.98	35.63	0.46	0.38	88.1	8.46	8.43	4.41
4	23,768	79.16	23.96	0.25	0.3	86.27	7.25	6.13	3.77
5	91,744	87.28	19.66	0.14	0.22	87.58	9.13	5.84	3.38

Table 3: Randomness of Transfer Policy

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
DV	Transfer at t[1]	Transfer at t	Transfer at t	Transfer at t	Transfer at t	Transfer at t	Transfer at t
A at t-1[2]	-0.251 (0.203)		-0.294 (0.206)				-0.0195 (1.199)
M at t-1[2]		0.342 (0.387)	0.429 (0.406)				-1.771 (2.916)
Tenure				-0.00199 (0.00139)			0.00960 (0.00850)
Female					0.368 (0.241)		1.645 (1.047)
Time since Last Transfer						0.151 (0.0957)	0.357 (0.282)
Intercept	-2.897*** (0.304)	-3.505*** (0.452)	-3.218*** (0.439)	-2.716*** (0.152)	-3.440*** (0.182)	-4.284*** (0.486)	-6.338* (3.493)
Period FE	Yes	Yes	Yes	No	No	No	Yes
N	2,603	2,646	2,590	3,224	1,947	696	150

[1]Logistic Regression (DV: Transfer, Indicator 1 if an officer is new to the branch at period t)

[2]Models 4 and 5 include Period FE, since incentive points at different periods cannot be directly compared.

Table 4. Internal Rate of Return (IRR) of Newly Originated Loans

	Model 1	Model 2	Model 3
DV	IRR	IRR	IRR
$\widetilde{AG}_{jo}$	-0.537***	-0.540***	-0.645***
	(0.152)	(0.152)	(0.159)
$\widetilde{R}_{j,o-1}$	-1.070**	-1.059**	-0.970*
	(0.538)	(0.538)	(0.567)
$\widetilde{AG}_{jo} * \widetilde{R}_{j,o-1}$		0.556	
		(1.382)	
$(\widetilde{AG}_{jo})^2$			-0.556**
			(0.244)
$(\widetilde{R}_{j,o-1})^2$			1.037
			(1.851)
$Transfer_{jo}$	1.987***	1.984***	1.988***
	(0.216)	(0.216)	(0.216)
Rating 2	3.991***	3.991***	3.995***
	(0.598)	(0.598)	(0.598)
Rating 3	13.33***	13.33***	13.33***
	(0.476)	(0.476)	(0.476)
Rating 4	21.74***	21.74***	21.75***
	(0.420)	(0.420)	(0.420)
Rating 5	26.66***	26.66***	26.66***
	(0.404)	(0.404)	(0.404)
Loan Amount	0.630***	0.630***	0.629***
	(0.0790)	(0.0790)	(0.0790)
Duration	-0.108***	-0.108***	-0.108***
	(0.0202)	(0.0202)	(0.0202)
Interest Rate	0.657***	0.657***	0.657***
	(0.00703)	(0.00703)	(0.00703)
Intercept	-10.95***	-10.97***	-10.87***
	(1.231)	(1.232)	(1.233)
Salesperson, Period FE	Yes	Yes	Yes
N	89,993	89,993	89,993

***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

Table 5. Delinquency of Existing Loans

	Model 1	Model 2	Model 3
DV	Delay	Delay	Delay
$\widetilde{R}_{j,t-1}$	0.0201*** (0.00763)	0.0203*** (0.00764)	0.0203*** (0.00778)
$Transfer_{jt}$	0.00448* (0.00257)	0.00442* (0.00257)	0.00442* (0.00257)
$Bad_{i,t-1}$	0.470*** (0.00198)	0.470*** (0.00198)	0.470*** (0.00198)
$Bad_{i,t-1} * \widetilde{R}_{j,t-1}$	-0.0954*** (0.0128)	-0.0957*** (0.0128)	-0.0957*** (0.0129)
$Bad_{i,t-1} * Transfer_{jt}$	-0.00403 (0.00390)	-0.00376 (0.00390)	-0.00377 (0.00391)
$\widetilde{AG}_{jt}$		-0.00440** (0.00178)	-0.00441** (0.00180)
$Bad_{i,t-1} * \widetilde{AG}_{jt}$		0.000994 (0.00321)	0.000999 (0.00322)
$\widetilde{AG}_{jt} * \widetilde{R}_{j,t-1}$			0.000431 (0.0169)
$Bad_{i,t-1} * \widetilde{AG}_{jt} * \widetilde{R}_{j,t-1}$			-0.000603 (0.0300)
Rating 2	-0.00468 (0.00415)	-0.00468 (0.00415)	-0.00468 (0.00415)
Rating 3	-0.0720*** (0.00351)	-0.0720*** (0.00351)	-0.0720*** (0.00351)
Rating 4	-0.165*** (0.00314)	-0.165*** (0.00315)	-0.165*** (0.00315)
Rating 5	-0.253*** (0.00301)	-0.253*** (0.00301)	-0.253*** (0.00301)
Loan Amount	-0.00482*** (0.000718)	-0.00483*** (0.000718)	-0.00483*** (0.000718)
Duration	0.00162*** (0.000180)	0.00163*** (0.000180)	0.00163*** (0.000180)
Interest Rate	0.00212*** (0.0000686)	0.00212*** (0.0000686)	0.00212*** (0.0000686)
Age of Loan	0.0113*** (0.000299)	0.0113*** (0.000299)	0.0113*** (0.000299)
Intercept	0.126*** (0.0112)	0.126*** (0.0112)	0.126*** (0.0112)
Salesperson, Period FE	Yes	Yes	Yes
N	278,943	278,943	278,943

***: p<0.01, **: p<0.05, *: p<0.1

Table 6: Total NPV of Originated Loans by Salesperson by Month

	Model 1	Model 2
DV	$\overline{\overline{NPV}}$	$\overline{\overline{NPV}}$
$\widetilde{AG}_{jo}$	2.390*** (0.264)	2.410*** (0.264)
$\widetilde{R}_{j,o-1}$	0.205 (0.924)	0.000635 (0.930)
$\widetilde{AG}_{jo} * \widetilde{R}_{j,o-1}$		-4.403* (2.431)
$(\widetilde{AG}_{jo})^2$		
$(\widetilde{R}_{j,o-1})^2$		
$Transfer_{jo}$	0.928*** (0.323)	0.941*** (0.323)
Intercept	4.957*** (1.885)	5.058*** (1.885)
Salesperson FE	Yes	Yes
Period FE	Yes	Yes
N	3,403	3,403

***: p<0.01, **: p<0.05, *: p<0.1

Table 7: IRR of Newly Originated Loans with Instrumental Variables

	Model 1
DV	IRR (IV)
$\widetilde{AG}_{jo}$	-0.705*** (0.167)
$\widetilde{R}_{j,o-1}$	-0.984* (0.567)
$Transfer_{jo}$	1.795*** (0.232)
Rating 2	5.473*** (0.735)
Rating 3	18.48*** (1.445)
Rating 4	29.81*** (2.191)
Rating 5	34.83*** (2.213)
Loan Amount	-2.962*** (0.967)
Duration	1.820*** (0.518)
Interest Rate	0.598*** (0.0176)
Intercept	-20.42*** (2.839)
Salesperson FE Period FE	Yes Yes
N	89,860

Table 8a: IRR of New Loans with Branch FE

	Model 1*	Model 2
DV	IRR	IRR
$\widetilde{AG}_{jo}$	-0.537***	-0.396**
	(0.152)	(0.158)
$\widetilde{R}_{j,o-1}$	-1.070**	-0.969*
	(0.538)	(0.572)
$Transfer_{jo}$	1.987***	2.177***
	(0.216)	(0.230)
Rating 2	3.991***	3.863***
	(0.598)	(0.609)
Rating 3	13.33***	13.02***
	(0.476)	(0.484)
Rating 4	21.74***	21.23***
	(0.420)	(0.427)
Rating 5	26.66***	26.09***
	(0.404)	(0.411)
Loan Amount	0.630***	0.619***
	(0.0790)	(0.0800)
Duration	-0.108***	-0.0923***
	(0.0202)	(0.0205)
Interest Rate	0.657***	0.662***
	(0.00703)	(0.00711)
Intercept	-10.95***	-8.615***
	(1.231)	(2.593)
Salesperson FE	Yes	Yes
Period FE	Yes	Yes
Branch FE	No	Yes
N	89,993	86,886

*Model 1 in Table 4

Table 8b: Delinquency of Existing Loans with Branch FE

	Model 1*	Model 2
DV	Delinquency	Delinquency
$\mathring{R}_{j,t-1}$	0.0203***	0.0193**
	(0.00764)	(0.00789)
$Transfer_{jt}$	0.00442*	-0.00454
	(0.00257)	(0.00425)
$Bad_{i,t-1}$	0.470***	0.470***
	(0.00198)	(0.00197)
$Bad_{i,t-1} * \mathring{R}_{j,t-1}$	-0.0957***	-0.0888***
	(0.0128)	(0.0132)
$Bad_{i,t-1} * Transf$	-0.00376	0.0229***
	(0.00390)	(0.00674)
$\overset{2}{\hat{A}}G_{jt}$	-0.00440**	-0.00503***
	(0.00178)	(0.00182)
$Bad_{i,t-1} * \overset{2}{\hat{A}}G_{jt}$	0.000994	0.00288
	(0.00321)	(0.00334)
Rating 2	-0.00468	-0.00554
	(0.00415)	(0.00418)
Rating 3	-0.0720***	-0.0730***
	(0.00351)	(0.00354)
Rating 4	-0.165***	-0.166***
	(0.00315)	(0.00317)
Rating 5	-0.253***	-0.255***
	(0.00301)	(0.00303)
Loan Amount	-0.00483***	-0.00478***
	(0.000718)	(0.000725)
Duration	0.00163***	0.00159***
	(0.000180)	(0.000181)
Interest Rate	0.00212***	0.00213***
	(0.0000686)	(0.0000692)
Age of Loan	0.0113***	0.0111***
	(0.000299)	(0.000301)
Intercept	0.126***	0.181***
	(0.0112)	(0.0509)
Salesperson FE	Yes	Yes
Period FE	Yes	Yes
Branch FE	No	Yes
N	278,943	274,907

*Model 2 in Table 5

***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

Table 9. Effect of Ratcheting Incentives

	Model 1	Model 2
	High*	Low*
DV	IRR	IRR
$\widetilde{AG}_{jo}$	0.690 (1.966)	-0.542*** (0.150)
$\widetilde{R}_{j,o-1}$	-8.032** (3.908)	-0.896* (0.539)
$Transfer_{jo}$	2.595 (1.811)	1.966*** (0.215)
Rating 2	-8.485** (3.755)	4.698*** (0.602)
Rating 3	2.026 (2.800)	14.03*** (0.481)
Rating 4	7.381*** (2.405)	22.56*** (0.425)
Rating 5	11.31*** (2.247)	27.54*** (0.409)
Loan Amount	-0.622 (0.588)	0.666*** (0.0789)
Duration	-1.378*** (0.138)	-0.0520** (0.0203)
Interest Rate	0.418*** (0.0514)	0.667*** (0.00703)
Intercept	30.32*** (6.149)	-12.68*** (1.220)
Salesperson FE	Yes	Yes
Period FE	Yes	Yes
N	3,414	86,579

*High (performers): Those whose Acquisition goal would have increased, if they performed on average.

***: p<0.01, **: p<0.05, *: p<0.1

Table A.1: Compensation Plan – Acquisition Goal[25]

Initial Portfolio Size	Jan 2009 – Jun 2009	Jul 2009 – Feb 2010
0 – 500,000	50,000	60,000
500,001 - 1,000,000	70,000	80,000
1,000,001 – 1,500,000	90,000	100,000
1,500,001 – 2,000,000	110,000	120,000
2,000,000 – 2,500,000	130,000	140,000
2,500,001 -	150,000	160,000

Table A.2: Compensation Plan – Maintenance Points

% loan amount in good standing	Maintenance Point	% loan amount in good standing	Maintenance Point
< 90%	0	97.91% - 99.49%	0.9
90.1% - 91.7%	0.5	99.5% - 100%	1
91.71% - 93.25%	0.6	100.1% - 100.5%	1.05
93.26% - 95.85%	0.65	100.51% - 101%	1.08
95.86% - 96.37%	0.7	101.1% - 101.5%	1.1
96.38% - 96.89%	0.75	101.51% - 102.5%	1.15
96.9% - 97.4%	0.8	102.6% - 103%	1.2
97.41% - 97.9%	0.85	103.1% -	1.25

[25] Acquisition Point (A) is the amount of acquired loans divided by Acquisition Goal.

Figure 1. The number of transfers

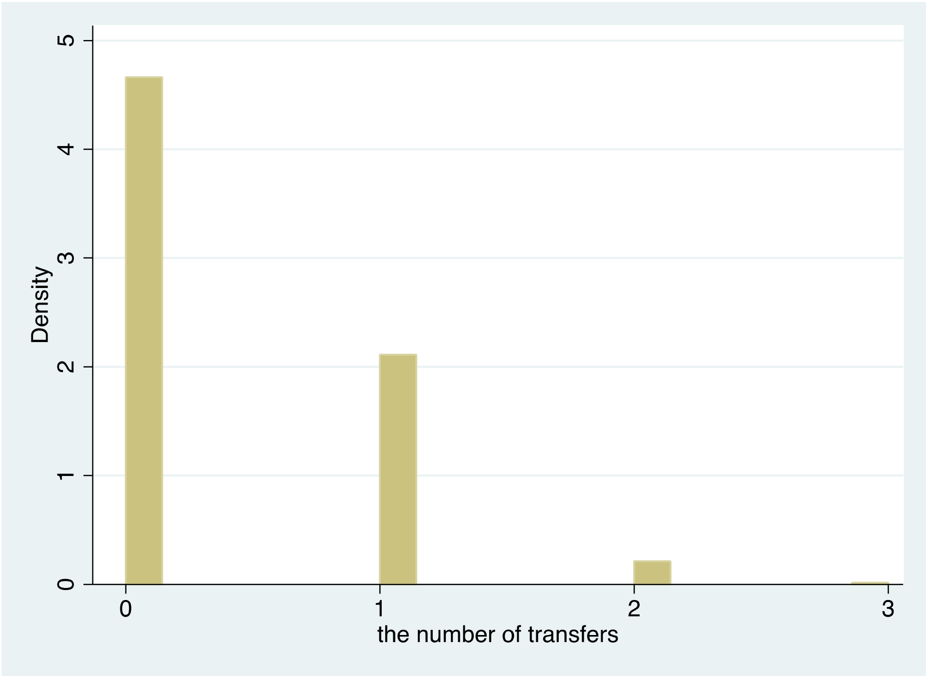

Figure 2. Profit under High vs. Low Retention Pressure