WHEN SALESPEOPLE MANAGE CUSTOMER RELATIONSHIPS:

MULTIDIMENSIONAL INCENTIVES AND PRIVATE INFORMATION

By

Minkyung Kim, K. Sudhir, Kosuke Uetake, Rodrigo Canales

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YALE UNIVERSITY
Box 208281
New Haven, Connecticut 06520-8281

http://cowles.yale.edu/

When Salespeople Manage Customer Relationships: Multidimensional Incentives and Private Information

Minkyung Kim,[1] K. Sudhir,[2] Kosuke Uetake,[3] Rodrigo Canales[4]

[1]Ph.D student, Yale School of Management, 165 Whitney Avenue, New Haven, CT 06511. Email: minkyung.kim@yale.edu
[2]James L. Frank '32 Professor of Private Enterprise and Management, Professor of Marketing & Director of the China India Insights Program, Yale School of Management, 165 Whitney Avenue, New Haven, CT 06511. Email: k.sudhir@yale.edu
[3]Assistant Professor of Marketing, Yale School of Management, 165 Whitney Avenue, New Haven, CT 06511. Email: kosuke.uetake@yale.edu
[4]Associate Professor of Organizational Behavior, Yale School of Management, 165 Whitney Avenue, New Haven, CT 06511. Email: rodrigo.canales@yale.edu

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Abstract

At many firms, incentivized salespeople with private information about customers are responsible for CRM. While incentives motivate sales performance, private information can induce moral hazard by salespeople to gain compensation at the expense of the firm. We investigate the *sales performance--moral hazard tradeoff* in response to multidimensional performance (acquisition and maintenance) incentives in the presence of private information. Using unique panel data on customer loan acquisition and repayments linked to salespeople from a microfinance bank, we detect evidence of salesperson private information. Acquisition incentives induce salesperson moral hazard leading to adverse customer selection, but maintenance incentives moderate it as salespeople recognize the negative effects of acquiring low quality customers on future payoffs. Critically, without the moderating effect of maintenance incentives, adverse selection effect of acquisition incentives overwhelms the sales enhancing effects, clarifying the importance of multidimensional incentives for CRM. Reducing private information (through job transfers) hurts customer maintenance, but has greater impact on productivity by moderating adverse selection at acquisition. The paper also contributes to the recent literature on detecting and disentangling customer adverse selection and customer moral hazard (defaults) with a new identification strategy that exploits the time varying effects of salesperson incentives.

Keywords: salesforce compensation, CRM, private information, adverse selection, moral hazard

INTRODUCTION

Firms increasingly recognize the value of customer relationship management (CRM) in that although acquiring customers is important, maintaining customer relationships—and ongoing revenue streams through higher customer lifetime value— is even more critical for a firm's overall profitability (Jain and Singh 2002, Shin and Sudhir 2010, Venkatesan and Kumar 2004). The academic literature on CRM has typically focused on settings where salaried marketers balance customer acquisition and maintenance goals using customer databases (e.g., Li, Sun and Montgomery 2011, Gupta and Lehmann 2005, Zhang, Netzer and Ansari 2014), but have generally ignored the common setting where firms use incentivized salespeople to acquire customers and maintain customer relationships.[1]

There are two major issues when incentivizing salespeople in CRM settings that have not been addressed in the sales incentives literature. First, we consider the need for *multidimensional performance based incentives* that balances sales from both new customer acquisition and existing customer retention and maintenance. But typical compensation plans that have been studied in the literature (e.g., Chung, Steenburgh and Sudhir 2014; Misra and Nair 2011) are only based on a unidimensional measure of performance such as total revenues, which do not decompose revenues arising from new customers as opposed to maintenance of existing customers--the core of CRM concepts of customer acquisition and retention.[2] Second, salespeople can have private information on customers, beyond publicly available information that is also known to the firm, through their relationships with customers. The private information can help the firm aid in improving customer acquisition and maintenance efficiency, but it may also be potentially used by salespeople to engage in *moral hazard* that improves their own compensation at the expense of the firm.

Our goal is to investigate the *sales performance--moral hazard tradeoff* among salespeople in the use of managerial levers related to *multidimensional incentives* and *private information* when salespeople manage customer relationships. First, the multi-dimensional incentive scheme rewards salespeople based on joint performance on the *acquisition* and *maintenance* dimensions. While acquisition metrics motivate salespeople to bring in sales through new customers, it also incentivizes them to commit moral hazard by selectively bringing in easier-to-acquire, poorer-quality customers with lower lifetime value. Firms can align salesperson acquisition behavior and address the moral hazard issue by appropriately weighting performance by customer quality if quality is observable to the firm (e.g., credit rating), but it is not feasible to do this with private information. Hence private information can hurt the firm through *customer adverse selection*.[3] Maintenance metrics incentivize salespeople to strengthen and maintain relationships to generate sales from previously acquired customers (e.g., through ongoing purchases/subscriptions, loan repayments etc.). But beyond this direct effect, it can also moderate the moral hazard by indirectly incentivizing forward looking salespeople to ex-ante not acquire bad customers, who are more difficult to retain (and therefore have lower CLV). By giving salespeople a stake in future cash flows from customers, maintenance incentives align firm and salesperson payoffs over the long-term, thus ameliorating the potential customer adverse selection motivation arising from acquisition incentives.

While the effects of acquisition and maintenance metrics in isolation are intuitive from the discussion above, their joint effects are harder to characterize. To help fix ideas, we develop a stylized analytical model of salesperson behavior in response to joint acquisition and maintenance incentives when they have private information about customers. Two key results arise. First, we find that given private information, salespeople engage in *advantageous customer* *selection* when there is high maintenance pressure (i.e. the prospect of existing customers bringing low profit in the future), and *adverse customer selection* when maintenance pressure is low. The result is insightful in that theoretically, maintenance incentives can not only ameliorate adverse selection, but even reverse it to obtain advantageous selection. What happens in practice is an empirical question. Second, and not surprisingly, customer maintenance performance always improves as maintenance pressure increases independent of acquisition incentives.

Second, we consider a lever that a firm can use to control the level of private information resident in salespeople, given the potential adverse selection effects of private information. One relevant lever in sales management that helps control the level of private information is periodic job transfers, that break customer-salesperson ties by relocating the salesperson to a new location with new customers.[4] While this can help the firm by reducing the cost due to adverse selection, it can also hurt the sales and maintenance efficiency gains from private information. Which of these effects dominate when there is a transfer is an empirical question.[5]

The above discussion on how private information and multidimensional incentives interact to produce a sales performance-moral hazard tradeoff makes it clear that the effect of multidimensional incentives and private information on customer selection, maintenance and overall productivity in CRM settings need empirical investigation. Accordingly, the paper addresses the following research questions relevant to salesforce management in CRM settings: (1) Do salespeople have private customer information? (2) Do acquisition incentives impact acquired customers' unobservable quality, and if so do they lead to advantageous or adverse customer selection? (3) Do maintenance incentives improve customer maintenance and how does it impact customer selection? (4) Do transfers that reduce private information improve or hurt the quality of customer selection and do they hurt or help customer maintenance? (5) Finally, what is the net effect of acquisition/maintenance incentives and transfers on overall productivity given the complex tradeoffs in terms of acquisition and maintenance efficiency, and selection effects?

Answering these questions poses a number of challenges. First, one needs matched panel data on salesforce 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 use unique panel-data from a microfinance bank in Mexico that lends to small business customers and allowed us 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 private information is challenging due to its intrinsic unobservability. Our primary identification strategy leverages the idea that, *conditional on public information*, salesforce performance metrics under the incentive scheme should not directly affect future consumer repayment behavior and profitability of new customers, but only indirectly through salespeople's efforts as *customers do not observe the metrics*. Empirically, we test if there is a systematic relationship between the salesperson's performance metrics, based on which the compensation is paid out, and the IRR of the acquired loans conditional on credit rating, loan characteristics, and various unobserved demand shifters.

Moreover, our empirical setting allows for exogenous variation in the level of private information, because the bank randomly transferred their salespeople, severing past relationships and private information about their customers. The policy is well-designed to be random and unpredictable so that salespeople cannot indulge in strategic behavior just prior to transfers.[6] The transfer policy allows us to understand how incentives interact with private information in producing customer acquisition, maintenance and overall productivity outcomes by comparing the salespeople's acquisition and maintenance behavior before and after the transfer.

We find that salespeople possess private information about customers and engage in moral hazard by using it to maximize their payoffs at the expense of the firm. The key takeaways from our findings are as follows: First, multidimensional incentives are critical to overwhelm the negative effects of moral hazard and obtain sales productivity gains in CRM settings. Salespeople "abuse" private information to acquire lower-quality customers conditional on observables to perform well on the acquisition metric, but the customer maintenance metric not only reduces loan defaults (better maintenance), but also indirectly moderates the adverse selection as forward looking salespeople anticipate the future consequences of current customer acquisition. It turns out that the overall impact on productivity from acquisition performance would not be positive without the joint use of maintenance incentives. Second, private information has positive efficiency enhancing effects, but the negative moral hazard effects on productivity are larger. When firms reduce private information and salesperson-customer relational capital using transfers,[7] the gain from a reduction in adverse selection is greater than the loss due to an increase in loan defaults as the relationships between the salesperson and borrowers is severed. Hence the periodic destruction of private information through transfers is a useful managerial lever in this setting.

The rest of the paper is organized as follows. We introduce how this paper is related to previous literature. Next, we describe institutional details and data. Third, we propose a stylized analytical model to formalize the idea. Fourth, we explain our empirical strategy and results and discusses the key findings. Lastly, we conclude and provide future research direction.

RELATIONSHIP TO THE LITERATURE

This paper contributes to multiple literatures in marketing and economics. As discussed in the introduction, the CRM literature has not addressed organizational issues of implementing CRM through an incentivized salesforce, and this paper addresses that important omission, given the ubiquity of sales force driven CRM across many industries.[8]

[Insert Table 1 here]

Our primary contribution is to the empirical literature on salesforce compensation, which we summarize based on the four columns Table 1. First, the existing empirical salesforce compensation literature (e.g., Chung, Steenburgh and Sudhir 2014; Misra and Nair 2011) either focuses on the situation where *one-shot transactions generate sales* or ignore the distinction between sales arising from new customers and those with existing relationships. This paper adds to the literature by examining the important case where *ongoing customer relationships matter* and therefore important to distinguish between sales from new customers versus sales from existing customers with whom there is already a relationship. Second, existing empirical salesforce compensation papers study *unidimensional* performance metrics. Although there have been a large number of empirical papers in the field of education and health on the multitasking agency problem (e.g., Feng Lu 2012, Neal and Schanzenbach 2010) since the seminal theoretical paper by Holmstrom and Milgrom (1991), to the best of our knowledge, our paper is the first empirical paper on salesforce compensation that studies a *multidimensional compensation scheme*.

Third, our paper introduces the issue of private information of salespeople as a source of salesperson moral hazard. Existing empirical papers consider salesperson moral hazard around the issue of *sales or effort timing problems* in response to nonlinear incentive plans involving bonuses and targets at periodic intervals. In contrast, we focus on salesperson moral hazard arising from *the existence of private information on customers*, which can lead to adverse customer selection in customer acquisition and/or delinquency due to inability to collect from those with whom there is strong relationship. In particular, our analytical model introduces a stylized framework that helps clarify the joint impact of acquisition and maintenance metrics on outcomes when there is private information. A key insight is that maintenance metrics can not only ameliorate adverse selection, but also lead to advantageous selection.

Fourth, our paper considers potential misalignments between a firm and its salesforce incentives in terms of information that is *unobservable* to the firm. In Larkin (2014), misalignment between the firm and its salespeople arises because the firm's performance metric does not take into account profit margins even though the firm can observe them, and salespeople offer excessive price discounts. In Copeland and Monnet (2008), potential misalignment between the firm and its workers is eliminated because the firm's performance metric weighs more the performance on difficult jobs. In these papers, at least conceptually, it is possible to address misalignment due to differences in true productivity based on *observables* by appropriately reweighting contemporaneous variables without concerns for *intertemporal effects*. In our paper, the firm faces a misalignment issue due to unobservable (or non-contractible) information and the nature of the misalignment is *intertemporal*. The maintenance incentive addresses the intertemporal misalignment by providing an ongoing stake in future cash flows from the "customer asset" through an effective "partial ownership" (Grossman and Hart 1986).

Our paper is also related to the literature on *social capital in organizations* (Sorenson and Rogan, 2014). As noted earlier, the private information residing within salespeople is a form of social relationship capital between the firm and its customers—an intangible asset whose ownership i.e., control and residual rights resides not with the firm, but with the salesperson (Grossman and Hart 1986). Recently, Shi et al. (2017) investigate the effect of sales representative departures on sales in a B2B setting and find that customer reassignment to different types of salespeople lead to customer churn with 13.2%-17.6% losses in annual sales for the firm, but this paper does not consider potential adverse selection effects. Canales and Greenberg (2015) show that these losses may be mitigated by replacing a sales representative with another who is stylistically similar in their interactions. These papers suggest that the salesperson-customer relationship is valuable to the firm for customer maintenance. Our paper shows that while this intangible asset (i.e., private ties that constitute relational contracts) is useful to firm in retaining and maintaining customers, its impact through salesperson moral hazard in customer acquisition can be high enough that its periodic destruction through transfers is profitable to the firm (Fisman, Paravisini and Vig 2011; Canales and Greenberg 2015).

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 customer moral hazard in insurance and credit markets. Note than in our empirical setting, loan defaults is a form of customer moral hazard. Identifying the existence of private information and quantifying its effect are challenging because of its intrinsic unobservability. Chiappori and Salanie (2000) initiated the literature and propose a positive correlation test to detect existence of asymmetric information in the car insurance market. Subsequent studies test for asymmetric information in health insurance, by obtaining access to additional information such as pre-existing conditions that cannot be lawfully used by insurance companies (Finkelstein and McGarry 2006, Finkelstein and Poterba 2004) to see if this information explains the type of insurance plans chosen by the individual and the ex-post health care consumption. The key issue is that researchers cannot disentangle whether the poor outcomes arise from ex-ante adverse selection or ex-post moral hazard by only observing ex-post customer behaviors.[9] 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). In a contemporaneous paper, Jeziorski et al. (2016) use the specific institutional rules of the Portuguese auto insurance market to address adverse selection and moral hazard. Our paper introduces 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 a policy that explicitly changes the level of private information about customers to separate customer adverse selection and customer moral hazard.

INSTITUTIONAL DETAILS AND DATA

In this section, we describe the institutional details of our empirical setting and then explain the data used in our empirical analysis.

Institutional Details

Our empirical application is in the context of a Microfinance Institution (MFI) in Mexico that provides collateral-free loans to low income, small business entrepreneurs through loan officers (salespeople). The loans are characterized by their small amount (median of $690), high interest rate (median rate is 85%), short maturity (average length is 6 months) and high delinquency probability (average of about 25.4%), as is common for microcredit institutions in emerging markets (see, e.g., Sengupta and Aubuchon (2008) for more discussion on microcredit loans in emerging markets).

Loan officers have two main responsibilities: acquiring new loans and ensuring repayments on existing loans. The acquisition stage involves recruiting borrowers through referrals or personal visits, accepting loan applications, and recommending loan terms to the bank. The bank uses public information about the borrower (i.e., a 1-5 credit rating with 5 as best, constructed with data from an external agency)[10] together with information in the loan application to both approve the loan and set the interest rate. Since a salesperson has a lot of discretion to approve a loan in our setting, she does not need to have a borrower take further actions if she wants to accept the loan. After acquisition, officers must ensure that loans are repaid on time (e.g., through phone calls and in-person visits). Throughout a loan's life, loan officers can create *relational capital* with their clients and use it to obtain private information about their motives, needs, financial capabilities/liabilities, and behavior. Salespeople can use such private information in loan decisions on top of observable variables (e.g., credit rating), because observables alone may not be sufficient to evaluate borrowers.[11] Our interest lies in how loan officers use this private information to enhance their personal income—either through increased efficiency in customer acquisition and maintenance that also benefits the firm or through adverse customer selection, which hurts the firm.[12]

The salesperson's compensation in the bank we study has two parts: salary and bonus. The salary is solely determined by seniority, not performance, while the bonus is a function of performance on both acquisition and customer maintenance. Acquisition performance is benchmarked against one's own past performance to create an acquisition index (A_{jt} for officer *j* at period *t* is defined by $A_{jt} = \frac{N_{jt}}{Q_{jt}^{A}}$, where N_{jt} is the amount of new loans acquired by office *j* at period *t*, and Q_{jt}^{A} is the acquisition quota, or the amount of active loans at period *t*). Maintenance performance is based on the number and value of loans collected relative to the loans outstanding as a maintenance index ($M_{jt} = \frac{R_{jt}}{LV_{jt}}$ where R_{jt} is the outstanding value of loans that are in good standing, and LV_{jt} is the outstanding value of loans in salesperson *j*'s portfolio due at period *t*. Hence $D_{jt} = 1 - M_{jt}$ is the fraction of the value of loans outstanding that is delinquent. The final bonus is the product of the base salary, acquisition index, and maintenance index (i.e., $Bonus_{jt} = Salary_{jt} \times A_{jt} \times M_{jt}$); 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 and introduces a dynamic trade-off for the salesperson: between the immediate benefits of acquiring (possibly 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. Such transfers are common in the retail banking sector to avoid the potential abuse of private information by loan officers, which could lead to adverse selection (e.g., Fisman, Paravisini and Vig 2011). Transferred salespeople take over and monitor the loans acquired by their predecessors who left the branch. The transferred salesperson's maintenance bonus does not depend on the loans she has collected in the previous branch, but solely depends on repayment outcomes of loans she took over after transfer. A particularly interesting characteristic of the transfer policy at the MFI is that the transfers, both in terms of timing and location, are entirely randomly determined. The randomness in timing is intended to prevent loan officers from engaging in greater adverse selection, when their expectations of transfer are high.[13] In the next subsection, we show that the transfers are indeed randomly determined. It allows us to treat transfers as an exogenous shock to salesperson private information.

Data

Our panel data include monthly salesforce performance and compensation data matched with the transactions on loans generated and maintained by the salespeople. 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). We do not observe rejected loans, but our empirical analysis does not rely on such information. Each loan can be matched with the loan officer who originated the loan, and with the loan officer who is 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 branch they were assigned to (from which we can infer transfers), and their score on the acquisition and maintenance benchmarks, which determined their bonus.

[Insert Tables 2a and 2b here]

Table 2a reports summary statistics of loan characteristics and bonus points. The average loan size is 9,192 pesos (approximately 690 US$ in 2009), with an average loan term of 6 months. The average (annual) interest rate is high at 87% as is typical in many emerging markets without collateral. The high interest rate reflects both a high overall delinquency rate of approximately 25.4% and high cost of acquiring and collecting loans.

The average of monthly acquisition points (A) is 0.75 and maintenance points (M) is 0.85; the average of the overall bonus multiplier ($A*M$) is 0.59 of the salary. Although we have significant missing values for the salary information, the average base salary is 4,050 Mexican pesos ($313 USD). Lastly, the average number of transfers is 0.37, with a maximum of three transfers over the 14 months we observe.

Next, we report on the relationship between the bank's credit rating of borrowers and loan performance. Recall that the bank's five-point rating of borrowers (1 least creditworthy to 5 most creditworthy) is determined by the central office and shared with the loan officers who place the loan and the loan underwriters who approve the terms of the loan. We confirmed that the delinquency probability falls and Internal Rate of Return (IRR) of a loan improves as the credit rating goes up, which indicates that the credit rating is a reliable predictor of borrower quality and the loan's risk and performance. Details on how we calculate the IRR can be found in the Appendix.

Table 2b further explores the relationship between credit rating and loan characteristics. 71% of the loans are given to those with credit rating of 5, 18% to those with credit rating 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. This is because the bank sets interest rates according to a policy where all first-time clients start at the highest rate, which is gradually lowered if clients maintain a good credit history. In contrast, duration of the loan is greater for those with lower credit rating, which may be the bank's attempt to make it feasible for borrowers with lower incomes to help pay back the loan.

During the observation window, 33.4% of officers had a transfer, and 3.2% had transfers more than once. To assess the randomness of the transfer policy, we report the results of logistic regression with transfer as a dependent variable, and observable officer characteristics as explanatory variables in Table 3. 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. Transfer is also not correlated with officers' past performances up to 3 months before transfer, or other officer characteristics, such as education level, marital status, relationship type (Canales 2013; Canales and Greenberg 2015) or position in the firm.

[Insert Table 3 here]

Analytical Model

We propose a stylized analytical model of salesperson behavior in response to acquisition and maintenance incentives as a function of current loan defaults in a salesperson's portfolio. The analytical model aims at setting formal structure to clarify the intuition underlying the verbal arguments laid out in the introduction and then understand the joint effects of acquisition and maintenance performance metrics on salesperson behavior. Given our focus on salesperson private information in the empirical analysis, the analytical model abstracts away observables about borrower quality (e.g., credit scores) and loan heterogeneity (e.g., loan amounts, duration), that are visible to both the firm and salesperson. Note that abstraction of these factors in the analytical model is equivalent to controlling for these factors in the empirical analysis (which we will do).

Customer Primitives

Prospective customers arrive periodically with requests for loans to a salesperson. The salesperson decides whether to offer a loan or not to each prospective customer given her incentive payoff and effort cost. There are two types of borrowers; a high type H who has a higher loan repayment probability (p_H) relative to the low type (p_L), i.e., $0 \leq p_L < p_H$. Further, we assume that loan delinquency is an absorbing state; i.e., a low type loan once delinquent is never repaid, i.e., $p_D = 0$. To reflect the idea that it is easier for salespeople to acquire low type customers,[14] we assume the arrival rate of low type customers λ_L is greater than that of the high type, i.e., $0 < \lambda_H < \lambda_L$. We normalize without loss of generality that $\lambda_L = 1$.

Salesperson Payoffs: Incentives and costs

The salesperson faces a multidimensional incentive based on acquisition and maintenance performance. Let B be the bonus, S the salary, A and M are the acquisition and maintenance metrics of performance. Consistent with our empirical setting, we use the following bonus function: $B = S * A * M$, where A is the number of loans acquired during the period, relative to one's quota for number of loans (Q), and M is the fraction of the loan portfolio that is not delinquent. Without loss of generality, we normalize S and Q to 1.[15]

Next we describe the cost of effort for acquisition and maintenance for the salesperson. To reflect the idea that greater effort is required to acquire a scarcer, higher value customer, we assume that the effort required for acquiring a customer of certain type is inversely proportional to their rate of arrival. Hence the cost of effort for acquiring a high and low type customer is $\frac{1}{\lambda_H}$ and $\frac{1}{\lambda_L}$respectively. Therefore if a salesperson acquires n_H high and n_L low type customers, the acquisition effort is given by $e_a = \frac{n_H}{\lambda_H}+\frac{n_L}{\lambda_L}$. Let $e_m = mp$ be the maintenance effort of a salesperson to obtain repayment probability of p from the low type that is not delinquent. Note that given the customer primitives above, maintenance effort cannot affect the probability of repayment of either the high type or the low type that is delinquent. The cost of effort in any given period is convex in the sum of acquisition and maintenance efforts, i.e.,$c(e) = \frac{c}{2}(e_a + e_m)^2$.

A key characteristic of the bonus scheme is that the maintenance metric (fraction of delinquent loans in salesperson's loan portfolio) induces inter-temporal forward-looking behavior by salespeople who anticipate how the mix of customers they acquire and the maintenance effort they incur to avoid delinquency in the present will affect their future compensation through its impact on the future delinquency rate. A complete characterization of the salesperson's acquisition and maintenance effort choices therefore requires solving a dynamic program, where the loan portfolio and default rate jointly evolve as a function of the mix of high and low type loans and the effort choices of the salesperson. Characterizing the analytic solution to such a dynamic program is non-trivial.

However, our goal of this analysis is more modest; to simply hypothesize whether acquisition and maintenance efforts are increasing or decreasing as a function of the value of the maintenance metric at the beginning of the period, i.e., share of delinquent loans in the loan portfolio. Our analytical strategy is therefore to solve for the salesperson choices for any arbitrary future continuation values of different loan types for the salesperson, such that their relative values satisfy constraints that are guaranteed to hold. Specifically let V_H,V_L and $V_D$denote arbitrary continuation values of salesperson payoff for a high type, low type and delinquent loan respectively. Given $1 = p_H > p_L > p_D = 0$, the order constraints $V_H > V_L > V_D$ will hold. As a normalization, we further assume $V_D = 0$.

Salesperson acquisition and maintenance choices

We now solve for salesperson choices in a period, conditional on the state of her portfolio at the beginning of the period. We characterize the portfolio in terms of its number of high, low and delinquent loans. Let *h* and *d* be the fraction of high type and delinquent loans respectively and let *k* be the total number of loans in the portfolio. Therefore the number of high, delinquent and low-non delinquent loans in the portfolio are *kh, kd*, and $k(1 - h - d)$ and respectively. Recall that high types do not become delinquent (i.e., $p_H = 1$), therefore all delinquencies occur from the low type.

As the firm does not observe loan types, but only the level of delinquents, maintenance incentives are only a function of loans that are delinquent (*d*). But the salesperson with private customer information can identify the borrower's type and acquire or maintain loans differentially by type. Given all borrowers are otherwise identical, a salesperson's choice in the acquisition stage is what fraction of arriving prospective borrowers to accept *by borrower type*. We denote the fraction as α_H for high type and α_L for low types. Given the rates of arrival, the number of borrowers accepted is $\lambda_H \alpha_H$ high types and α_L low types. In the maintenance stage, a salesperson with private information will only monitor low types who are not delinquent as high types always repay and delinquent loans never repay. For a monitoring intensity of p, as described earlier, the repayment probability of the low type is $p_L = p$.

Now we compute the salesperson's net current period payoff given bonus and cost of effort. The acquisition metric of performance is the number of acquired loans divided by quota (normalized to 1) i.e., $\lambda_H \alpha_H + \alpha_L$. The maintenance metric of performance is the fraction of loans repaid, i.e., $h + (1 - h - d)p$. Given the multiplicative bonus scheme, the salesperson bonus is $(\lambda \alpha_H + \alpha_L) * (h + (1 - h - d)p)$. The effort required to acquire $\lambda_H \alpha_H + \alpha_L$is $\alpha_H + \alpha_L$. The maintenance effort required to obtain repayment probability p from the low types is given by *mp*. Thus the total effort given by $e = \alpha_H + \alpha_L + mp$ and cost of effort is $\frac{c}{2} e^2$.

The salesperson with private information chooses acquisition rates by type (α_H, α_L) and monitoring level p so as to maximize the sum of the current period payoff and the continuation value of payoffs from existing loans:

$$U(\alpha_H, \alpha_L, p) = (\lambda_H \alpha_H + \alpha_L) * (h + (1 - h - d)p) - \frac{c}{2}(\alpha_H + \alpha_L + mp)^2$$
$$+[(\lambda_H \alpha_H + kh)V_H + (\alpha_L + k(1 - h - d)p)V_L]$$
$$\text{s.t. } 0 \leq \alpha_H, \alpha_L, p \leq 1$$

The solution consists of the optimal acquisition rate by type α_H^* and α_L^*, and monitoring level p^*. We now state the key propositions from our analysis. To help understand the effects of private information, we begin with a benchmark result on customer acquisition for the symmetric information case, where neither salesperson nor firm has private information.

Lemma: Customer selection in acquisition without private information: When there is no private information, the acceptance rate of low type and high type customers will be equal, i.e., $\frac{\alpha_L^*}{\alpha_H^*}$*=1. The ratio of number of low to high types among newly acquired customers* $\frac{\alpha_L^*}{\lambda\alpha_H^*}$ *will equal the ratio of the arrival rates of the two types* $\left(\frac{1}{\lambda}\right)$*, irrespective of the level of delinquent loans at the beginning of the period.*

The lemma is intuitive. Without any private information on types, salespeople accept all customers at the same rate, and their relative share is entirely determined by the arrival rates of these customers.

Proposition 1: Customer selection in acquisition with salesperson private information

(i) *As share of delinquents in the salesperson's loan portfolio* (d) *at the beginning of the period increases, the ratio of low types to high types among newly acquired borrowers in the period* $\frac{\alpha_L^*}{\lambda\alpha_H^*}$ *decreases till it reaches zero, at which point, only high types are acquired.*

(ii) *There exists a threshold level of share of delinquent loans in the portfolio* d^**, above which the ratio of low types to high types among newly acquired customers* $\left(\frac{\alpha_L^*}{\lambda\alpha_H^*}\right)$ *is lower than the symmetric case, i.e.,* $\left(\frac{\alpha_L^*}{\lambda\alpha_H^*}\right) < \left(\frac{1}{\lambda}\right)$*, i.e., there is advantageous selection relative to the symmetric* *case. In contrast, below* d^**, there is adverse selection in new customer acquisition, i.e.,*

$\left(\frac{\alpha_L^*}{\lambda\alpha_H^*}\right) > \left(\frac{1}{\lambda}\right)$.

Proof: In Appendix.

Figure 1 illustrates the proposition with a numerical example for the case of $\lambda = 0.4, k = 0.45, c = 0.65, m = 0.01, V_L = 0.25, V_H = 1.625, h = 0.6$. Figure 1a shows that the share of low types decreases and that of high types increases as d goes up. In Figure 1b, there is a threshold level of d^*at which the share of low to high types crosses the "no private information" share of low to high types $\left(\frac{1}{\lambda}\right)$, indicating the shift from adverse selection to advantageous selection.

The proposition states that when salespeople have higher maintenance pressure (higher share of delinquent loans in portfolio), they bring fewer easier to acquire "low type" customers. Whether private information will lead to adverse selection or advantageous selection will depend on a threshold level of d, below (above) which private information leads to adverse (advantageous) selection in acquisition.

Proposition 2: Ex-post (after acquisition) maintenance effort and loan delinquency

As the share of delinquent loans d *in the salesperson's portfolio increases, their maintenance effort increases. The resulting probability of loan defaults falls monotonically with d, i.e.,* $\frac{\partial p^*}{\partial d}$*>0.*

Proof: In Appendix.

The proposition states that as maintenance pressure in the form of higher share of defaults in loan portfolio increases, salespeople increase their monitoring effort *p*, and reduce the probability of loan defaults for the low types p_L. For the same parameters as in the earlier numerical example, Figure 1c shows that monitoring effort *p* increases in *d*.

[Insert Figures 1a, 1b and 1c here]

EMPIRICAL ANALYSIS

We first discuss the identification strategy and then outline steps of the empirical analysis.

Identification Strategy

Given that a salesperson's private information is inherently unobservable, it is challenging to demonstrate its presence or identify its effects on salespeople's performance outcomes. Our identification strategy relies on two ideas (1) that customers do not observe the salesperson's incentive based motivation driving customer acquisition and maintenance efforts and (2) transfers exogenously change the level of salesperson's private information about customers.

First, if a salesperson has no private information, the profitability of newly acquired loans (IRR) should not systematically change with the salesperson's acquisition performance or maintenance pressure at the time of acquisition, after *conditioning on observable characteristics such as loan terms and macro shocks.* Thus any effect of acquisition performance or maintenance pressure on customer acquisition helps identify private information.

Second, the transfer policy creates variation in the level of private information among salespeople with transferred people having less private information or relational capital with their customers. The randomness in the policy makes this variation exogenous. Therefore, by comparing the the IRR of newly acquired loans between transferred and continuing officers, controlling for other observables and fixed effects helps identify the effect of private information on customer acquisition. Similar comparison of the probability of delinquency of existing loans helps identify the effect of private information during the maintenance period. Whether the private information leads to advantageous/adverse selection at customer acquisition or increase/reduce defaults at the maintenance stage remains an empirical question.

Empirical Strategy

Our empirical analysis proceeds in three steps. First, we examine selection effects on the quality of loans due to managerial levers: acquisition/maintenance incentives, and transfers. This allows us to test for both the existence of private information and empirically assess how multi-dimensional incentives and transfers impact customer selection. Second, we examine *ex-post* repayment/delinquency behavior in response to the managerial levers. Finally, we examine the effects of the levers on overall salesperson productivity. We complement our main results with robustness checks. All reported specifications are available in the Web Appendix.

Acquisition: Selection Effects When Originating Loans

We investigate the selection effects during customer acquisition as a function of (1) acquisition performance, (2) maintenance pressure and (3) transfer state of the salesperson *at the time of origination of the loan* (denoted by o). We estimate the following panel linear regression model

$$(1) \qquad IRR_{ijo} = \alpha_1 + \beta_1 \tilde{A}_{jo} + \beta_2 \widetilde{D}_{j,o-1} + \gamma_1 Transfer_{jo} + \gamma_2 X_i + \mu_j + \phi_o + \epsilon_{ijo}$$

In equation (1), IRR_{ijo} is the internal rate of return of loan i, originated by officer j, at time o. IRR_{ijo} measures loan performance realized after the loan cycle. To eliminate the effects of cross-sectional variation across salespeople and focus on intra-salesperson states, we demean acquisition performance (A_{jo}) by salesperson average across all periods to obtain $\tilde{A}_{jo}$. Similarly we demean the fraction of the value of delinquent loans in salesperson j's portfolio at t (D_{jt}) by salesperson average across all periods to obtain $\widetilde{D}_{jt}$. As we explained in the analytical model, the maintenance pressure in period o is based on the fraction of delinquent loans at the end of the previous period o-1, so we include $\widetilde{D}_{jo-1}$ in the regression. The dummy variable $Transfer_{jo}$ equals 1 if officer j was new to the branch at the origination period, which we operationalize as working at the branch for less than a month.[16]

The model controls for observable loan characteristics in X_i, such as the borrower's credit rating, loan amount, duration, and interest rate. The model also includes loan officer fixed effects to control for unobserved heterogeneity in salespeople, such as risk-aversion, leniency or effect of quotas. Lastly, the model has time fixed effects to capture any macro-level shocks, such as competition against other banks or macroeconomic shocks. We abstract away from potential concerns of endogeneity in the loan terms for now, but revisit this issue in the robustness checks section.

We are primarily interested in coefficients β_1, β_2 and γ_1. The coefficients β_1 indicates how unobservable loan quality changes with acquisition performance, controlling for all observable borrower and loan characteristics. A negative β_1 indicates adverse customer selection as the salesperson seeks out privately known "bad" customers who are easier to acquire to improve acquisition performance. A positive β_2 implies that adverse selection is moderated by the maintenance incentive and that officers are forward-looking, i.e., officers under high maintenance pressure screen out unprofitable borrowers at o to prevent a higher delinquency risk in the future. Lastly, the coefficient γ_1 shows the effect of the transfer policy. A positive γ_1 shows that continuing officers acquire worse loans than transferred officers, suggesting that salespeople with little private information (relational capital) engage less in adverse selection. Note that transferred and continuing salespeople likely differ in their incentive quotas and information levels. γ_1 indicates the pure effect of change in the level of information due to a transfer, since we control for their incentive states, $\tilde{A}_{jo}$ and $\widetilde{D}_{j,o-1}$ in the specification.

[Insert Table 4 here]

Table 4 reports the results. In Model 1, we find that a one-point increase in acquisition performance relative to the loan officer's average leads to 0.54% decrease in the IRR of new loans. A one-point increase in the maintenance pressure leads to a 1.07% increase in IRR of new loans. Transferred officers, whose private information is eliminated, bring in higher-quality loans by 2% of IRR. This shows evidence of private information among the salesforce, that higher acquisition performance accentuates adverse selection, maintenance pressure mitigates adverse selection, and transfers also mitigate adverse selection. We additionally examine loan performance measures beyond IRR, such as the number of late repayments and the failure to collect a loan on time at least twice during the loan cycle, and found qualitatively similar results. Those results are available from the authors upon request.

Model 2 adds an interaction term between the two incentive states, while Model 3 includes quadratic terms for them to capture potential nonlinear effects. 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 riskier borrowers. The coefficients of other variables are in the expected direction. As observable credit rating increases, IRR goes up. Smaller loan amounts, longer durations, and higher interest rates are associated with lower profitability.

Finally, in an unreported specification, we test if transferred salespeople who do not have private information engage in less adverse selection even as they increase their acquisition performance. Indeed that interaction effect is positive, supporting the hypothesis.

Maintenance: Ex-post Loan Repayment

Next, we investigate how maintenance pressure and transfers impact ex-post repayment behavior or delinquency *at the maintenance stage*. Loan officers under high maintenance pressure are expected to increase monitoring to reduce defaults on repayment. However, transferred officers without private information may perform worse on this dimension as they have less information to targeting their maintenance effort, where they are most needed. Hence, we run the following regression.

$$(2)\ Delinquency_{ijt} = \alpha_1 + \beta_1 \tilde{A}_{jt} + \beta_2 \widetilde{D}_{j,t-1} + \gamma_1 Transfer_{jt}$$

$$Bad_{it-1}(\alpha_2 + \beta_3 \tilde{A}_{jt} + \beta_4 \widetilde{D}_{j,t-1} + \gamma_2 Transfer_{jt}) + \gamma_3 X_{it} + \mu_j + \phi_t + \epsilon_{ijt}$$

Note that the equations (1) and (2) examine salespeople's behavior at different stages (acquisition stage denoted as "*o*" and maintenance stage is denoted as all subsequent periods after acquisition, generically denoted by "*t*"). In Equation (2), $Delinquency_{ijt}$ is a dummy indicating delinquency of loan *i*, under loan officer *j*, at time *t*. A key part of the maintenance model in equation (2) is that it separately examines the effects on loans that are already delinquent at the end of *t-1*, which is represented by the indicator Bad_{it-1} (i.e. $Bad_{it-1} = 1$) and those that are repaid on time in period *t-1* (i.e. $Bad_{it-1} = 0$). We do so because a salesperson's monitoring may have greater impact on loans that are not currently delinquent (i.e. $Bad_{it-1} = 0$), as we find in the data that delinquent loans tend to remain delinquent irrespective of loan officer actions. We then examine the effect of the maintenance pressure and the transfer policy for each group of borrowers. The model also controls for loan characteristics through X_{it} and officer and period fixed effects through μ_j and ϕ_t, respectively.

The main coefficients of interest are those related to maintenance pressure, which primarily incentivizes salespeople to ensure repayments on loans. A positive β_2 shows that salespeople under high maintenance pressure increase monitoring intensity to improve borrowers' repayment behavior at *t*. A positive γ_1 indicates that the removal of private information when the salesperson was transferred just prior to period *t* increases delinquency at *t*; suggesting that relational capital and the private information that results from it does help target efforts on the right borrowers and ensure repayment.

[Insert Table 5 here]

The estimates are reported in Table 5. Model 1 has only maintenance pressure at *t*, Model 2 has both acquisition and maintenance states, and Model 3 adds the interaction of the two components. The coefficient of $\widetilde{D}_{j,t-1}$ is negative and significant in Models 1, 2 and 3, indicating that maintenance pressure improves monitoring and reduces delinquency of *good* loans. Specifically, a one-unit increase in maintenance pressure in period *t* , leads to a 2% decrease 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 the elimination of private information through transfers prevents effective monitoring and hurts loan repayment by 0.4%. The negative coefficient of $\tilde{A}_{jt}$ in Model 2 indicates that performance on acquisitions is complementary to that on maintenance due to the multiplicative form of the incentive structure. A large coefficient on $Bad_{i,t-1}$ suggests that loans that are delinquent are more likely to remain so. Thus, under high maintenance pressure, officers are less likely to monitor such loans and more likely to focus on loans currently in good standing. The positive coefficient of $Bad_{i,t-1} * \widetilde{D}_{j,t-1}$ suggests that currently delinquent loans receive less monitoring and are more likely to remain delinquent under high maintenance pressure. We find that transfers have little effect on bad loans, because continuing salespeople also do not exert significant effort to maintain those borrowers. We confirm that our results are robust to alternative definitions of *Bad loans*.

In sum, combining the findings from the estimates of equations (1) and (2), we find that private information plays different roles in the acquisition and maintenance stages. In the acquisition stage, continuing salespeople with private information engage in adverse selection, which hurts the firm's profit, evidenced by the positive γ_1 in equation (1). However, the negative

γ_1 in the equation (2) shows that their information advantage leads to more effective monitoring at the maintenance stage, which reduces defaults and increases the firm's profit.

Salesperson Productivity: Total Net Present Value of Loans Generated

Thus far, we have found evidence of salesperson moral hazard that results in customer adverse selection due to acquisition incentives. Maintenance incentives mitigate this adverse selection, and also improve customer repayment. Transfers which reduce private information reduce adverse selection, but also hurt customer repayment. This is a very rich set of empirical effects. However, the central question in the use of these levers remains. What is the net effect on the incentives and transfers, on overall salesforce productivity? For this, we examine whether the sales-enhancing effect of the incentive levers (e.g., Chung, Steenburgh and Sudhir 2014) exceeds the negative adverse selection effect due to private information, and whether the positive effect of transfer (decrease in adverse selection) exceeds the negative effect (ineffective monitoring). We analyze salesperson productivity at the *salespeople-month level* rather than at the loan-level to allow for sales expansion effects.[17] In particular, we run the following model in equation (3).

$$(3)\ NPV_{jo} = \alpha_1 + \beta_1 \tilde{A}_{jo} + \beta_2 \widetilde{D}_{j,o-1} + \beta_3 \left(\tilde{A}_{jo} * \widetilde{D}_{j,o-1}\right) + \gamma_1 Transfer_{jo}$$
$$+\gamma_2 X_i + \mu_j + \phi_o + \epsilon_{ijo}$$

The dependent variable 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*.

[Insert Table 6 here]

Table 6 reports the regression results. Model 1 is the baseline case and the estimates show β_1 is positive, β_2 positive, and γ_1 positive and the effects are all statistically significant. These results imply that each of the levers considered contribute positively to firm profits. However we need to consider the interaction between the acquisition and maintenance stages to understand how these incentives jointly affect profitability. Model 2 adds an interaction term between acquisition points and maintenance states, illustrated in Figure 2. When the salesperson is under high maintenance pressure (i.e., those whose previous-period maintenance points are 0.5 point below their average), the greater acquisition performance leads to a sharp increase in profits, but when the maintenance pressure is low (0.5 point above their average), an increase in acquisition points leads to very little increase in profits. In the absence of maintenance pressure, salespeople engage in significant adverse selection, which neutralizes profits from customer acquisition. In effect, the firm is paying out commissions with little gains in profitability. However, officers avoid risky acquisitions under high maintenance pressure, which contributes to the firm's profits. This shows that, without the use of maintenance metrics of performance that penalize ex-post delinquency, salespeople will resort to significant adverse selection and hurt firm profitability.

[Insert Figure 2 here]

Managerial Implications

Our analytical approach and our findings around private information and multidimensional incentives have important managerial implications for sales force compensation and management. Our simple regression based approach to evaluate how current incentive plans at an organization can affect customer acquisition, retention and aggregate salesforce productivity in the presence of private information can be widely used. We note that while our application is in a setting of multidimensional incentives where the salesforce is responsible for both customer acquisition and retention, the acquisition and productivity regressions can also be used when salesforces are only incentivized for acquisition, to measure adverse selection effects and the net productivity effects (sales expansion-adverse selection trade-off) of the incentives.

Next we discuss how our findings provide guidance for salesforce management. First, while it is well-appreciated by managers that the sales expanding benefits of acquisition incentives are accompanied by moral hazard costs (salespeople can choose actions for private gain at the expense of the firm), the conventional wisdom is that the sales expanding benefits should more than overwhelm the moral hazard costs. Surprisingly, in our application we find that without the disciplining effects of maintenance metrics on salesforce moral hazard, the overall benefits from acquisition incentives can be negative because of adverse selection and lack of attention to retention. This suggests that the cost of salesforce moral hazard and remedies should be evaluated more seriously by sales management in settings even when only acquisition incentives are currently offered. In particular, we highlight the role of transfers when feasible as way to "kill" private information in order to reduce salesperson moral hazard. While our results justify the oft-employed transfer practices in retail banking,[18] we note that the net effects of transfers will vary across settings. Our approach however provides a general approach for managers to study the net effects of transfers in other settings.

Second, an often-used remedy for firm-salesforce misalignment is to appropriately weigh performance metrics to create alignment. For instance, if salespeople discount heavily to win sales and improve revenue performance, weighing the revenues by margins can create alignment. But weighting may not always be feasible, and our findings suggest that multidimensional performance metrics may be the more feasible option to create alignment. For example, in the context of CRM it is well-known that retention often matters more than even acquisition for firm value. While weighting acquired customers by CLV is a possibility, it is often infeasible because (i) CLV requires forecasts of future retention and revenues, and it may not be feasible to tie incentives to forecasts and (ii) it is not possible to hold the salesperson responsible for future retention, once payments have been made based on forecasts. Multidimensional incentives where incentives balance current acquisition and future maintenance performance are a very effective managerial solution in these settings without requiring future forecasts.

Finally, our findings have implications for job design in CRM settings. Firms implementing CRM often use a hunter-farmer model where some salespeople are responsible for customer acquisition (hunting), while others are responsible for customer maintenance (farming), to take advantage of the benefits of specialization in skills needed for these two types of activities. Our results suggest that the gains from specialization may be overwhelmed by the moral hazard at customer acquisition due to customer adverse selection. Our results suggest that it may be useful to create teams with joint responsibility for acquisition and maintenance, to benefit from the gains in specialization,while simultaneously internalizing the potential for moral hazard.

CONCLUSION

This paper aims at addressing the challenges of the sales performance-moral hazard trade-off arising when salespeople manage customer relationships. We consider the role of multidimensional incentives that are based on joint acquisition and maintenance metrics and that of private information. A stylized analytical model of salesperson behavior in CRM settings helps us understand how the acquisition and maintenance jointly impact outcomes when there is private information. We then exploit unique matched panel data on customers and salespeople at a microfinance organization to empirically analyze how these sales management levers impact CRM outcomes. Managerially, our study illustrates how firms managing CRM can assess the effect of their performance metrics and compensation plans on customer acquisition, retention and overall productivity. This approach can be used even firms only use acquisition performance incentives by estimating only the customer acquisition and productivity regressions. Methodologically, the paper also introduces a new identification strategy to detect and disentangle customer adverse selection and customer moral hazard that has been a major issue in credit and insurance markets, by exploiting time-varying effects of loan officer incentives and job transfers.

We believe this paper is a first step to address a rich set of research issues at the intersection of CRM and sales management. We conclude with some suggestions for future research. First, we considered a setting involving customer acquisition for loans and ongoing repayment for the loan's life. Insurance settings are similar in that they also involve customer acquisition of insurance policies and ongoing premium payments over the life of the policy. But other common settings do not have clear maintenance outcomes--for example CRM often involves cross-selling of products, increasing the share of a customer's wallet etc. Further research is needed on how firms should incentivize salespeople on such CRM related metrics.

Second, substantive research on multidimensional incentives is still scarce. While multidimensional incentives involve balancing short-run and long-run considerations with acquisition and maintenance incentives in our paper, firms may want to align employee incentives by weighing competing contemporaneous considerations (e.g., lowering service time and increasing satisfaction) in other settings.

Third, in finance, transfers are commonly used as a means to render the salesperson's relational capital unusable and thus minimize negative effects of adverse selection in customer acquisition. However, this can potentially hurt the efficiency gains from the ongoing relationship. Canales and Greenberg (2015) find that much of the potential loss of repayment of loans may be averted by replacing salespeople with others who have a similar relational style, suggesting that there may be a way to reduce customer adverse selection through transfers, while avoiding the increased loan defaults through continuity in salespeople styles. More generally, while we find that transfers have a net benefit for the bank, Shi et al. (2017) find in their setting that customer reassignment to salespeople (equivalent to transfers) can lead to significant loss churn in the context of electrical product retailer. However, Shi et al. does not consider the adverse selection issue. Future research may investigate how the relative importance of adverse selection vs. efficiency from private information varies across industries and how managers can balance them.

Finally, our results should motivate more research on sales person job design in CRM settings. While in bank and insurance settings, salespeople are responsible for both customer acquisition and maintenance, many organizations and industries follow a specialized hunter-farmer model (Palmatier et al. 2007) with different employees responsible for customer acquisition (hunt) and customer retention/maintenance (farm). In such cases, we suggest that to the extent possible, a CLV weighted metric of performance should be used to incentivize hunters, while the farmers be incentivized on maintenance metrics. Alternatively, one may construct teams that are responsible for both acquisition and retention, thus gaining both specialization benefits while reducing the cost of moral hazard. But more broadly, our research suggests that when designing organizations for CRM, we need to balance the efficiency gain from specialization in acquisition and maintenance activities, with the potential adverse effects that we identify arises from the separation of those tasks.

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ENDNOTES

1. Related papers at the sales management-CRM interface include (1) Kumar, Sunder and Leone (2014), who propose a metric to compute salesperson lifetime value based on CLV managed by each salesperson, and (2) Palmatier et al. (2007) and Shi et al. (2016) who study the linkages between salesperson turnover and customer loyalty. These papers do not address incentive issues.

2. A natural question is whether one could use aggregate CLV aggregate CLV of a salesperson’s acquired customers in a period as unidimensional metric to determine incentives. Two practical challenges arise. First, CLV requires forecasting future revenues of customers, but incentive contracts based on forecasts is often infeasible. Further, the salesperson has little incentive to deliver the forecast CLV by retaining customers after having received the incentive.

3. The issue of adverse selection in response to sales incentives has received much media attention in 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 creditworthiness in order to receive loan acquisition bonuses as they were not responsible for subsequent performance. 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 a salesperson knowingly acquires customers who

are likely to leave soon before the acquisition costs have been recouped, such acquisitions can hurt firm value.

4. Employee transfer is a common practice in the B2B finance sector. France, Germany, and the U.S., for example, mandate rotation of audit partners across clients. See discussion in Fisman, Parvasini and Vig (2011) on mandated transfers in the Indian state banking sector.

5. Firms typically do not have levers either contractually or through incentives to appropriate this asset from the salesperson so that the firm can avoid the adverse selection. For instance, although firms encourage salespeople to input information about their ongoing conversations with prospects and stage of conversion in CRM tools, salespeople are reluctant to part with this information, which they view as their own assets for which they receive no rewards for sharing.

6. Hertzberg, Liberti, and Paravisini (2010) find that loan officers are more likely to make negative reports on borrowers' ability to repay, when anticipating transfers. The randomization of transfers in our setting excludes the possibility of such strategic behavior by officers.

7. We do not distinguish between private information and relational capital. Both are established as a salesperson interacts with potential customers and existing customers (borrowers) over time, at the time of loan application, screening, monitoring and repayment. Thus we treat transferred salespeople as those who lost both private information and relational capital.

8. Reinartz, Krafft and Hoyer (2004) consider issues of organizational alignment in implementing CRM, but do not consider salesforce incentive issues.

9. The relationship between loan officers' incentives and their screening/monitoring behaviors have been studied in finance (Agarwal and Ben-David 2014; Cole, Kanz and Klapper 2015; Heider and Inderst 2012; Hertzberg, Liberti and Paravisini 2010). They mention problems with unidimensional incentives but do not formally address the balance between multiple tasks.

10. Loan officers cannot change credit ratings, nor do they advise customers about how to improve credit ratings. Since a salesperson has significant discretion in approving the loan in our setting, she does not need to make a borrower to take further action to recommend the loan.

11. Based on interviews, Canales (2013) notes that salespeople do not completely trust observables, and tend to act based on private information. We quote from two interviews: (1) "*You (a loan officer) go through the entire analytic process and, at the end, if you trust the client and believe in her, you give her the loan. Maybe the liquidity index will not be enough [according to the rules] but if you believe in her, you will "help her out" and you will take the risk with her." and (2)* "*They (officers) have access to information on each of their clients. They can use that information to determine the moral and economic solvency of new prospects, to detect when a client is in trouble, and to be more effective when they need to collect. They have seen what works and what doesn't. They know who does what and who knows who. When officers use that information to benefit a client, they can make a big difference."*

12. Our data allows us to study repayment behavior within a loan, but we lack sufficiently long panel data to study customer retention and repayment behavior across loans. Further, maintenance incentives are only for repayment. Therefore we only consider repayment within the loan as maintenance.

13. As salespeople are given less than one week to start work at the new location after a transfer it is hard for them to change their behavior or share private information to incoming salespeople.

14. This is because observably high type customers have more outside options due to greater competition for their business (see Jeziorski et al. 2016 for such evidence in car insurance market).

15. We check the robustness of our hypotheses for an additive bonus function and find them to be qualitatively robust in the Web Appendix.

16. We use the one month operationalization for "newness to branch" because: 1) given short loan cycles, salespeople seek to elicit as much information as possible in a short time and 2) salespeople work for 14-15 hours a day, thus typically get to know their customers within the month. Our results are robust to alternative operationalizations of newness.

17. The total NPV metric is similar in spirit to the Salesperson Lifetime Value Metric in Kumar, Sunder and Leone (2015) at the salesperson-month level, but with ex-post *known* (as opposed to *forecast*) values of future customer cash flows.

18. We note that the effects of transfers can vary by context, by the specifics of the transfer policy used, and the nature and use of private information in that context. Like in our paper, Shi et al. (2017) show that transfers break the relationship between employees and customers and increase customer churn rate, but it is possible that the adverse selection costs of private information may be weaker in other settings.

Table 1. Previous Literature on Salesforce Compensation

Paper	**Transaction/ Relationship**	**Performance Metric Uni/Multi dimensional**	**Salesperson Moral Hazard (Hidden action)**	**Firm/Agent Misalignment as performance metric not weighted by observables**
Oyer (1998)	Transactional (Sales)	Unidimensional: Annual revenue targets	Moral Hazard: Find evidence that sales timing shifts to reach quota	
Misra and Nair (2011); Kishore,Rao, Narasimhan and John (2013)	Transactional	Unidimensional: Quarterly revenue targets with ratcheting	Moral Hazard: Find evidence that sales timing shifts to reach quota	
Chung, Steenburgh and Sudhir (2014)	Transactional	Unidimensional: Quarterly and annual revenue targets with non-ratcheting quotas	Moral hazard: Finds evidence that sales timing shifts to reach quota, but can be minimized through overachievement commission and non-ratcheting quotas	
Larkin (2014)	Transactional	Unidimensional: Annual revenues	None	Misalignment: Salespeople discount price as performance metric does not account for observable margins
Copeland and Monnet (2008)	Transactional	Unidimensional: No of checks sorted daily as a weighted function of task difficulty	Moral Hazard: Find evidence that effort timing shifts based on distance to quota	**Reduce misalignment *within* periods**: Weighting observable job difficulty leads to right effort allocation within day
This paper	**Relationship (distinguish new and existing customers)**	**Multidimensional**: Function of monthly loan acquisition and loan repayment	**Moral hazard: due to customer private information** * Advantageous/Adverse customer selection? * Customer maintenance?	**Reduce misalignment *across* periods**: Future maintenance concerns discourage easier, low quality (low credit rating) customer acquisition

Table 2a. 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			
Salesforce 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 2b. 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[1]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
DV	$Transfer_t$	$Transfer_t$	$Transfer_t$	$Transfer_t$	$Transfer_t$	$Transfer_t$	$Transfer_t$
A_{t-1}	-0.251		-0.294				-0.0195
	(0.203)		(0.206)				(1.199)
M_{t-1}		0.342	0.429				-1.771
		(0.387)	(0.406)				(2.916)
Tenure				-0.00199			0.00960
				(0.00139)			(0.00850)
Female					0.368		1.645
					(0.241)		(1.047)
Time since Last Transfer						0.151	0.357
						(0.0957)	(0.282)
Intercept	-2.897***	-3.505***	-3.218***	-2.716***	-3.440***	-4.284***	-6.338*
	(0.304)	(0.452)	(0.439)	(0.152)	(0.182)	(0.486)	(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] We run logistic regression (DV: Transfer, Indicator 1 if an officer is new to the branch at period t).

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

	Model 1	Model 2	Model 3
DV	IRR	IRR	IRR
$\tilde{A}_{jo}$	-0.537*** (0.152)	-0.540*** (0.152)	-0.645*** (0.159)
$\widetilde{D}_{j,o-1}$	1.070** (0.538)	1.059** (0.538)	0.970* (0.567)
$\tilde{A}_{jo} * \widetilde{D}_{j,o-1}$		-0.556 (1.382)	
$(\tilde{A}_{jo})^2$			-0.556** (0.244)
$(\widetilde{D}_{j,o-1})^2$			1.037 (1.851)
$Transfer_{jo}$	1.987*** (0.216)	1.984*** (0.216)	1.988*** (0.216)
Rating 2	3.991*** (0.598)	3.991*** (0.598)	3.995*** (0.598)
Rating 3	13.33*** (0.476)	13.33*** (0.476)	13.33*** (0.476)
Rating 4	21.74*** (0.420)	21.74*** (0.420)	21.75*** (0.420)
Rating 5	26.66*** (0.404)	26.66*** (0.404)	26.66*** (0.404)
Loan Amount	0.630*** (0.0790)	0.630*** (0.0790)	0.629*** (0.0790)
Duration	-0.108*** (0.0202)	-0.108*** (0.0202)	-0.108*** (0.0202)
Interest Rate	0.657*** (0.00703)	0.657*** (0.00703)	0.657*** (0.00703)
Intercept	-10.95*** (1.231)	-10.97*** (1.232)	-10.87*** (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
$\widetilde{D}_{j,t-1}$	-0.0201***	-0.0203***	-0.0203***
	(0.00763)	(0.00764)	(0.00778)
$Transfer_{jt}$	0.00448*	0.00442*	0.00442*
	(0.00257)	(0.00257)	(0.00257)
$Bad_{i,t-1}$	0.470***	0.470***	0.470***
	(0.00198)	(0.00198)	(0.00198)
$Bad_{i,t-1} * \widetilde{D}_{j,t-1}$	0.0954***	0.0957***	0.0957***
	(0.0128)	(0.0128)	(0.0129)
$Bad_{i,t-1} * Transfer_{jt}$	-0.00403	-0.00376	-0.00377
	(0.00390)	(0.00390)	(0.00391)
$\tilde{A}_{jt}$		-0.00440**	-0.00441**
		(0.00178)	(0.00180)
$Bad_{i,t-1} * \tilde{A}_{jt}$		0.000994	0.000999
		(0.00321)	(0.00322)
$\tilde{A}_{jt} * \widetilde{D}_{j,t-1}$			-0.000431
			(0.0169)
$Bad_{i,t-1} * \tilde{A}_{jt} * \widetilde{D}_{j,t-1}$			0.000603
			(0.0300)
Rating 2	-0.00468	-0.00468	-0.00468
	(0.00415)	(0.00415)	(0.00415)
Rating 3	-0.0720***	-0.0720***	-0.0720***
	(0.00351)	(0.00351)	(0.00351)
Rating 4	-0.165***	-0.165***	-0.165***
	(0.00314)	(0.00315)	(0.00315)
Rating 5	-0.253***	-0.253***	-0.253***
	(0.00301)	(0.00301)	(0.00301)
Loan Amount	-0.00482***	-0.00483***	-0.00483***
	(0.000718)	(0.000718)	(0.000718)
Duration	0.00162***	0.00163***	0.00163***
	(0.000180)	(0.000180)	(0.000180)
Interest Rate	0.00212***	0.00212***	0.00212***
	(0.0000686)	(0.0000686)	(0.0000686)
Age of Loan	0.0113***	0.0113***	0.0113***
	(0.000299)	(0.000299)	(0.000299)
Intercept	0.126***	0.126***	0.126***

	(0.0112)	(0.0112)	(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	NPV_{jo}	NPV_{jo}
$\tilde{A}_{jo}$	2.390*** (0.264)	2.410*** (0.264)
$\widetilde{D}_{j,o-1}$	-0.205 (0.924)	-0.000635 (0.930)
$\tilde{A}_{jo} * \widetilde{D}_{j,o-1}$		4.403* (2.431)
$Transfer_{jo}$	0.928*** (0.323)	0.941*** (0.323)
Intercept	4.957*** (1.885)	5.058*** (1.885)
Salesperson FE Period FE	Yes Yes	Yes Yes
N	3,403	3,403

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

Figure 1a. Acceptance rate by Type under Private Information

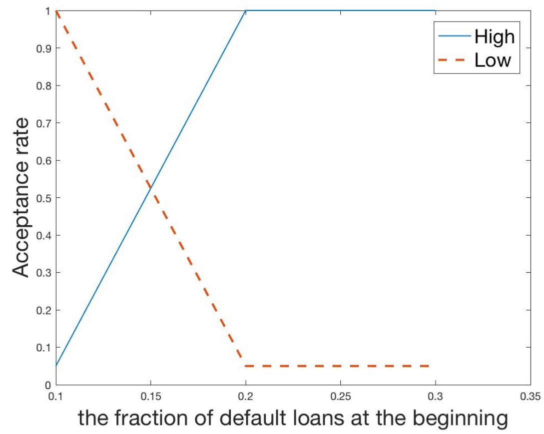


Figure 1b. Relative acceptance rate (Low/High) under Private information vs. No information

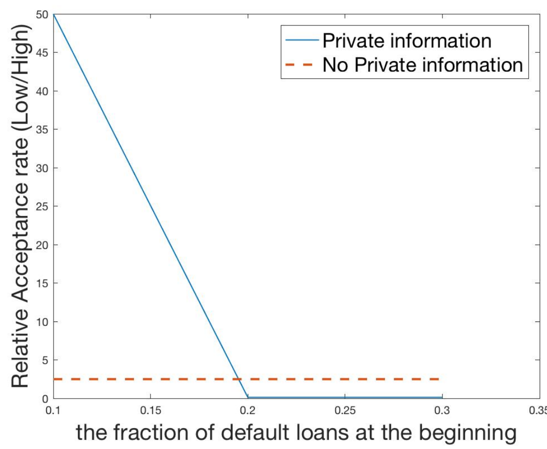
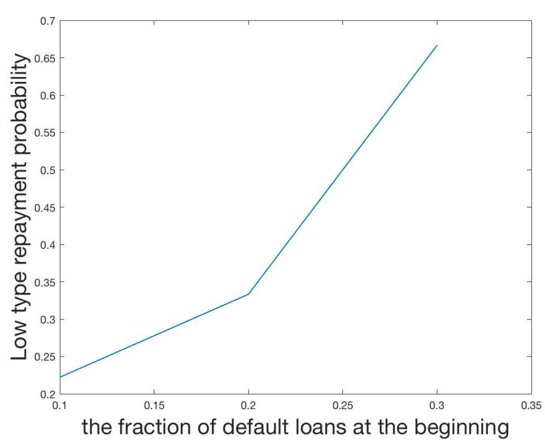
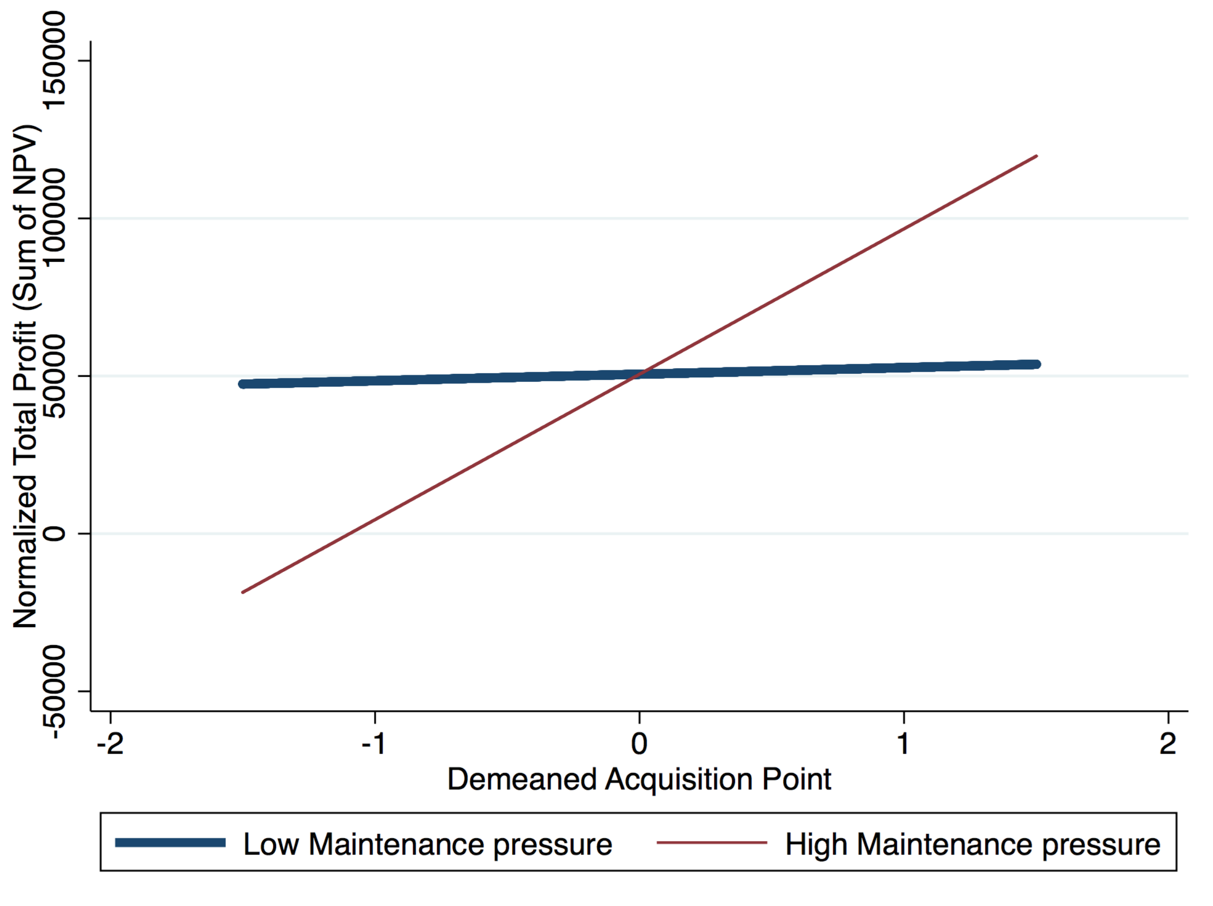


Figure 1c. Monitoring Intensity under Private Information



*Optimal behavior under $\lambda = 0.4, k = 0.45, c = 0.65, m = 0.01, V_L = 0.25, V_H = 1.625, h = 0.6$

Figure 2. Profit under High vs. Low Maintenance Pressure



Appendix

Details on Compensation Plan

We describe the specifics of how acquisition and maintenance points are calculated for the purposes of compensation. Tables A.1 describes how a sales person's target for a month is set based on the portfolio size of the previous month. Acquisition point (A) is the ratio the value of newly acquired loans to acquisition target as defined in Table A.1. Table A.2 describes the nonlinear mapping from percentage of loan amount in good standing to maintenance points.

[Insert Tables A.1 and A.2 here]

Formal Analytical Model

We provide the details of the analytical model. We solve for the optimal action for a salesperson to maximize the objective function. Only the interior solutions are presented here but the corner solutions (0 or 1) are applied under some conditions.

$$\alpha_H^* = \frac{1}{c(1-h-d)^2(1-\lambda)^2}[(1-h-d)^2(V_H\lambda + V_L(ck(1-\lambda)-\lambda)) - cm(h^2(1-\lambda)$$

$$+(c+2(1-d))V_H\lambda - cV_L - (1-d)(1+\lambda)V_L - h(1-d+c(1-\lambda)-\lambda(1-d)+2V_H\lambda$$

$$-V_L(1+\lambda))) + c^2m^2(V_H\lambda - V_L - h(1-\lambda))]$$

$$\alpha_L^* = \frac{1}{c(1-h-d)^2(1-\lambda)^2}[-(1-h-d)^2(V_H\lambda^2 + V_L(ck(1-\lambda)-\lambda^2)) + cm\lambda((1-h$$

$$-d)(V_H(1+\lambda)$$

$$-h(1-\lambda) - 2V_L) - c(h(1-\lambda) - V_H\lambda + V_L)) + c^2m^2(-V_H\lambda + V_L + h(1-\lambda))$$

$$p^* = \frac{\lambda(V_H+h) - (V_L+h)}{(1-\lambda)(1-h-d)}$$

Proof of Proposition 1.

$$\frac{\partial}{\partial d}\left(\frac{\alpha_L^*}{\lambda\alpha_H^*}\right) < 0 \text{ when } d < \frac{(1-h)\lambda^2(V_H-V_L)^2+c(V_H\lambda-V_L-h(1-\lambda))(V_{\square}\lambda(1-m)+V_Lk(1-h)(1-\lambda)-\lambda(1-m))}{c\ h\ k\ V_L(1-\lambda)^2\ +(V_H^2\lambda^2-V_H\lambda V_L(ck(1-\lambda)+2\lambda)-(\lambda^2+ckV_L^2(1-\lambda)))}$$

$$+\frac{(c^2\lambda^2(1-\lambda)^2(V_H-V_L)^2(h(1-\lambda)-V_H\lambda+V_L)^2(1-m)+c^3kV_Lm(1-\lambda)^3(h(1-\lambda)-V_H\lambda+V_L)^3(1-m))}{c\ h\ k\ V_L(1-\lambda)^3\ +\ (1-\lambda)(V_H^2\lambda^2-V_H\lambda V_L(ck(1-\lambda)+2\lambda)-(\lambda^2+ckV_L^2(1-\lambda)))}$$

$\frac{\alpha_L^*}{\lambda\alpha_H^*} > \frac{1}{\lambda}$ (e.g. adverse selection) or $\alpha_H^* < \alpha_L^*$ when

$$d < \frac{1}{2\lambda(1-\lambda)(V_H-V_L)+4ckV_L(1-\lambda)}[2\lambda(1-h)(1\ +\ \lambda)(V_H-V_L)+ckV_L(4\ (1-\ h)(1-\lambda)$$

$$+\ (\ h\ (1\ +\lambda^2)$$

$$+(1+3\ \lambda)V_L-V_H\lambda\ (3+\ \lambda))m)+cm(m(8(V_H\lambda-V_L-h(1-\lambda))(V_H\lambda(1+\lambda)$$

$$+V_L(2ck(1-\lambda)-\lambda(1+\lambda))+(1-\lambda)({V_H}^2\lambda^2(1-\lambda)+h^2(1-\lambda)(1+\lambda)^2-2V_HV_L\lambda(1-\lambda-8ck)$$

$$-(1-\lambda+16ck){V_L}^2+2hV_L(1-\lambda)(V_H\lambda(1+\lambda)+(1+\lambda+8ck)))^{1/2}]$$

$\frac{\alpha_L^*}{\lambda\alpha_H^*} < \frac{1}{\lambda}$(e.g. advantageous selection) or $\alpha_H^* > \alpha_L^*$ when d is greater than the threshold.

Proof of Proposition 2. $\frac{\partial p^*}{\partial d} = \frac{\lambda(V_H+h)-(V_L+h)}{(1-\lambda)(1-h-d)^2} > 0$ since $\lambda(V_H+h)-(V_L+h) > 0$

Table A.1: Compensation Plan – Acquisition Target

Portfolio Size	01/09 – 06/09	07/09 – 02/10	Portfolio Size	01/09 – 06/09	07/09 – 02/10
0 – 500,000	50,000	60,000	1,500,001 – 2,000,000	110,000	120,000
500,001 - 1,000,000	70,000	80,000	2,000,000 – 2,500,000	130,000	140,000
1,000,001 – 1,500,000	90,000	100,000	2,500,001 -	150,000	160,000

Table A.2: Compensation Plan – Maintenance Point

% loan amount in good standing	Point	% loan amount in good standing	Point	% loan amount in good standing	Point
0 - 87.5%	0	93 - 93.5%	0.75	96.5 - 97%	1.05
87.5 - 88.5%	0.5	93.5 - 94%	0.8	97 – 97.5%	1.08
88.5 - 90%	0.6	94 - 94.5%	0.85	97.5 - 98%	1.1
90 - 92.5%	0.65	94.5 - 96%	0.9	98 - 99%	1.15
92.5 -93%	0.7	96 - 96.5%	1	99 - 99.5%	1.2
				99.5 - 100%	1.25

Web Appendix (Not for Publication)

Further evidence on the randomness of transfer policy

In the main text, we argue that transfer decisions are completely random, verified by interviews with the firm and our analysis in Table 3 in the paper. In this section, we additionally confirm that the transfer decisions are not correlated with the average loan amount that each salesperson gives out, or the interaction between time since the last transfer and previous period's maintenance performance. The result reported in Table WA1 shows that no coefficient is significant at the 10% level and verifies the randomness of transfer policy.

[Insert Table WA1 here]

Duration of the Effect of Transfer

In the main text, we assume a salesperson as new to the branch, if he has worked for the branch for less than a month. Our assumption stems from the fact that 1) loan cycles are very short (i.e. 6 months on average), thus salespeople tend to try to elicit much information about customers in a short time and 2) salespeople typically work for 14-15 hours per day, thus might have enough time to get to know a new set of customers in a month.

In order to see how long it takes for a salesperson to get familiar with her new area, we check another definition of "new" loan officers. The variable $Transfer_{jo}$ is defined as the dummy variable indicating that a salesperson j has been in the branch for less than *two* months as of the period o. In Table WA2, we find that at the acquisition stage, the effects of $\tilde{A}_{jo}$ and $\widetilde{D}_{j,o-1}$ remain qualitatively consistent, but the Transfer effect becomes statistically insignificant. As we argued earlier, we believe that 2-months is already a very long time in this setting, considering the loan cycle and salespeople's working hours. Thus, the new definition dilutes the effect of transfer policy that gets rid of private information from salespeople.

[Insert Table WA2 here]

Table WA3 reports our analysis at the maintenance stage. The variable $Transfer_{jt}$ is defined as the dummy variable indicating that a salesperson j has been in the branch for less than two months as of the period t. As in the main analysis in the paper, we find the negative coefficient of $\widetilde{D}_{j,t-1}$, implying the maintenance pressure ramps up monitoring intensity and reduces loan defaults among loans in good standing in the previous period (i.e. $Bad_{i,t-1}$ = 0). Also, the transferred salespeople do less effective monitoring, but the magnitude of the effect gets smaller. The coefficient of $Transfer_{jt}$ in Table 5 is 0.00442, whereas the coefficient goes up to 0.00541 with the new definition. All other coefficients remain qualitatively consistent with our main analysis documented in Table 5 in the paper.

[Insert Table WA3 here]

Analytical Model Under Additive Incentive Scheme

In our empirical context, the bank uses a multiplicative compensation scheme, where acquisition and maintenance performance indices are multiplied to compute bonuses. Accordingly, our hypotheses in the main paper were based on a model using a multiplicative compensation structure. We now assess whether our hypotheses will continue to hold an additive compensation scheme, by changing the compensation scheme in Section 3.

All assumptions and notation remain the same as in Section 3. The only change is that we the total bonus is now based on the sum of acquisition and maintenance performance. The salesperson maximizes the sum of the current period's bonus and her loans' continuation value, considering the acquisition and monitoring costs, as she does under the multiplicative incentive scheme.

$$U(\alpha_H, \alpha_L, p) = (\lambda_H \alpha_H + \alpha_L) + (h + (1 - h - d)p) - \frac{c}{2}(\alpha_H + \alpha_L + mp)^2$$

$$+[(\lambda_H \alpha_H + kh)V_H + (\alpha_L + k(1-h-d)p)V_L]$$

$$\text{s.t } 0 \leq \alpha_H, \alpha_L, p \leq 1$$

We solve for the optimal solution of acquisition rate by type α_H^* and α_L^*, and monitoring level for low type p^*. The solutions are provided below.

$$p^* = (m(1+V_L) - (1-h-d)(kV_L+1))/(cm(m-1))$$

$$\alpha_H^* + \alpha_L^* = (V_L(k-1) - (kV_L+1)(h+d))/c(m-1)$$

Both the hypotheses from the Analytical Model section, continue to remain valid.

Details on Calculating Internal Rate of Return

In this section, we explain how to calculate the internal rate of return (IRR), which is a key outcome variable in our main empirical analysis. The IRR of each loan is calculated 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. IRR of loan *i* is defined as the rate that makes the loan's NPV zero.

$$NPV_i = \sum_{t=1}^{T} \frac{C_{it}}{(1+r)^t} - C_{io}$$

Here, C_{it} is cash inflow in the period t (either full amount to be repaid, or zero amount), C_{io} is loan size, r is the interest rate and T is the number of time periods to be considered. If a borrower does not default, T is equal to the loan's maturity, otherwise T is the number of periods before default.

Robustness Check - Endogeneity In Branches Where The Officers Are Transferred

In the main paper, we demonstrate that the transfer was indeed random (Table 3). Nevertheless, even if the transfer policy is random, it may be possible that officers in under-performing branches are more likely to be transferred to higher-performing branches or branches faced with better market conditions. If so, transferred officers may face a more profitable customer base in a new branch; thus, her new loans might perform better, and this may have nothing to do with the elimination of adverse selection due to private information. To address this concern, we include branch fixed effects and re-estimate coefficients in equations (1) and (2).

Tables WA4 and WA5 show that our main results remain robust with branch fixed effects. Model 1 shows the estimates from Tables 4 and 5 in the main paper without branch fixed effects for comparison. For the acquisition stage regression reported in Table WA5, we continue to find evidence of adverse selection due to acquisition incentives and moderation of adverse selection due to maintenance incentives. The incentive states have smaller effect on IRR in Model 2 than in Model 1, since now the effect of branch-level market conditions (i.e., overall quality of customer base in a branch) on loan performance is controlled. Even including brand fixed effects, the coefficient of $Transfer_{jo}$ remains positive, showing that transfers reduce adverse selection — transferred officers bring in higher quality loans than do continuing officers, even conditional on branch-level unobserved heterogeneity.

Table WA5 documents salespeople's monitoring behavior within a branch. While the main loan default effects of incentives remain robust, the maintenance incentive effects are smaller with branch fixed effects, for both good and bad loans. In Model 2, the effect of transfer is insignificant for good loans, and slightly positive for bad loans, indicating that transferred salespeople without private information are not very effective in monitoring existing loans, particularly bad loans.

[Insert Tables WA4 and WA5 here]

Robustness Check - Endogeneity in Loan Terms

In our main specification, we treated loan terms as exogenous. A salesperson, however, may adjust loan terms (amount and maturity) using her private information. In order to address this concern, we redo the analysis, by using instruments for loan amount and loan duration to account for potential endogeneity. Recall that the interest rate is set by the bank as a function of the credit rating.

We use the average loan characteristics of other loans acquired by the same loan officer *j* at period *o* as instruments for loan characteristics. Our rationale for the instruments is as follows: The average loan terms of a loan officer conditional on their observed loan rating in any given period reflect both the general style of the loan officer and his/her incentive based motivations in that period in offering loan terms. These factors are thus independent of any private information that the salesperson has on the customer and thus its impact on ex-post profitability and therefore is a valid instrument. Table WA6 shows that our instruments have sufficiently large F-values and are correlated with endogenous variables in the first stage.

We report the results of the IRR regression with instruments in Table WA7. Interestingly, the effects of the main variables of interest, Acquisition, Maintenance and Transfers on IRR remain the same, but now the adverse selection effects have larger magnitudes and the maintenance pressure and transfer effects have smaller magnitudes. First, this shows that there is indeed endogeneity of loan terms. Further, it shows that the endogeneity of loan terms attenuate the effects of acquisition incentives and strengthens the effects of maintenance pressure and transfers on IRR. Further, we find a reversal of signs for the terms loan amount and duration in Model 2. Specifically, we find that larger loans have lower IRR and larger duration loans have lower IRR. This suggests that salespeople offer larger loan amounts and longer duration loans to consumers about whom they have negative private information, conditional on other observed characteristics.

[Insert Table WA7 here]

We assess robustness based on an additional instrument for loan amounts and duration based on the loan amount and duration offered by the same salesperson to other customers with the same credit rating as the current customer. While this is more closely related as an instrument given that we additionally condition on customer observables, the challenge is that the number of such matched loans by customer types and salesperson tends to be often very few. In our setting, there are about 42 loans on average served by the same officer in the same month, but only about 24 loans on overage with the same credit rating and served by the same officer in the same month.

Nevertheless, the results remain qualitatively robust as seen in Table WA8. The F-value confirms that the instruments work well. We still find the adverse selection when a salesperson acquires more customers, and is a continuing officer in the same branch. The effect of maintenance pressure ($\widetilde{D}_{j,o-1}$) has the same positive sign, but becomes insignificant at the 10% significance level with the duration instrument. We partly attribute this finding to fewer matched cases.

[Insert Table WA8 here]

Robustness Check - Interaction between Incentive States and Transfer

In the main text, we find evidence that transferred officers do not have private information and thus are less likely to engage in adverse selection. In other words, the adverse selection is expected to go down for transferred salespeople, if we include the interaction between Transfer dummy and Acquisition performance and observables. We report the results of such a specification in Table WA9. We find all main findings remain consistent: a salesperson engages in adverse selection due to acquisition incentive, the effect is moderated due to maintenance pressure, and the transfer to a new branch induces a salesperson to acquire higher quality borrowers. The positive coefficient of the interaction between acquisition incentive and transfer dummy tells us that the adverse selection due to acquisition incentive goes down for transferred salespeople. This is consistent with our theory and expectation that customer adverse selection will be greater for continuing salespeople who have more private information about customers.

[Insert Table WA9 here]

Robustness Check - Salesperson Learning

We test additional specifications to rule out the explanation that a salesperson learns about how to increase IRR of customers over time in general. In Table WA10, we examine the effect of the dummy variable indicating the acquisition increases in column 1, and split the data based on whether the acquisition increases or not in columns 2 and 3. In Table WA11, the model controls for each salesperson's tenure (i.e. years since he/she joined the institution). We still find that a salesperson is more likely to engage in adverse selection when her acquisition performance goes up, mainly when $\tilde{A}_{jo}$ is positive in column 2 of Table WA10. Other variables in interest show consistent results. The adverse selection is mitigated under higher maintenance pressure and the transferred officers are more likely to accept safer loans. In Table WA11, the positive coefficient of *Tenure* variable shows that the experience at the bank helps the salesperson acquire better quality customers.

[Insert Tables WA10 and WA11 here]

Further, a salesperson might learn about customers in a particular region over time after moving to a new branch, and the increase in information affects loans' profitability. We examine if any change in a salesperson's private information about a region drives our qualitative result on IRR. We measure how many quarters have passed since transfer (i.e. since a salesperson started to work in a new branch) and interact the term with Incentive states, Transfer states and Salesperson fixed effects. In Table WA12, the most variables in interest are in effect. The table below shows that most variables in interest are still in effect. The first column interacts the quarter FE with Incentive states, the second column interacts the quarter FE with Incentives states and Transfer states, and the third column interacts the quarter FE with Salesperson FE to accommodate time-varying unobserved heterogeneity across salespeople.

[Insert Table WA12 here]

We interpret these results as follows. While is possible for a salesperson to improve his/her ability to increase IRR as they learn about a region (greater efficiency), private information can lead to losses in IRR as salesperson brings in easy to acquire low type consumers, conditional on observables. We define private information as any information about customer profitability beyond credit rating or the firm's observables. If a salesperson learns about how to increase IRR of general customers or customers in a particular region, but still engages in adverse selection, it strengthens our argument that private information induces salespeople to acquire lower-quality customers.

Acquisition Target Ratcheting

In Table A.1 of the appendix, we describe how the bank sets its acquisition targets. As can be seen, in the quota schedule, a larger starting portfolio can lead to larger acquisition targets, with discrete jumps above discrete thresholds. One may wonder whether our results are robust to ratcheting effects.

Observe that ratcheting incentives will not change our qualitative conclusions. The ratcheting effect leads to a perverse incentive for a salesperson who has just met current acquisition targets to not exceed the threshold, so as not to have a higher target the following month. This means that in the face of ratcheting incentives, adverse selection incentive is marginally mitigated. In other words, our measured estimate of adverse selection in response to acquisition incentives is a lower bound.

Previous empirical literature on salesforce compensation has highlighted the adverse consequences of ratcheting incentive that induces workers to withhold effort to avoid larger future quotas (e.g., Anderson, Dekker and Sedatole 2010; Misra and Nair 2011). Our results shed new light on the another effect of ratcheting by alleviating customer adverse selection; disciplining salespeople to avoid the abuse of asymmetric information for short-term compensation at the expense of the firm. This effect may be a rationale for the use of target in practice (e.g., Leone and Rock 2002; Weitzman 1980).

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Table WA1. Randomness of Transfer Policy

	Model 1	Model 2
DV	$Transfer_t$	$Transfer_t$
M_{t-1}	-0.0480 (0.203)	
Time since Last Transfer	-0.0116 (0.0146)	
M_{t-1} * Time since Last Transfer	0.0157 (0.0159	
Average Loan Amount		0.0384 (0.0357)
Intercept	0.0405 (0.0716)	-0.0122 (0.0164)
Period FE	Yes	Yes
N	659	3,448

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

Table WA2. Internal Rate of Return (IRR) of Newly Originated Loans with a new definition of the Transfer dummy

DV	IRR
$\tilde{A}_{jo}$	-0.504*** (0.152)
$\widetilde{D}_{j,o-1}$	1.129** (0.538)
$Transfer_{jo}$	0.00570 (0.193)
Intercept	-9.196*** (1.227)
Loan Characteristics	Yes
Salesperson, Period FE	Yes
N	89,993

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

Table WA3. Delinquency of Existing Loans with a new definition of the Transfer dummy

	Model 1
DV	Delay
$\widetilde{D}_{j,t-1}$	-0.0202*** (0.00764)
$Transfer_{jt}$	0.00541** (0.00214)
$Bad_{i,t-1}$	0.469*** (0.00205)
$Bad_{i,t-1} * \widetilde{D}_{j,t-1}$	0.0943*** (0.0128)
$Bad_{i,t-1} * Transfer_{jt}$	0.00516 (0.00318)
$\tilde{A}_{jt}$	-0.00453** (0.00178)
$Bad_{i,t-1} * \tilde{A}_{jt}$	0.00111 (0.00321)
Intercept	0.126*** (0.0112)
Loan Characteristics	Yes
Salesperson, Period FE	Yes
N	278,943

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

Table WA4: IRR of New Loans with Branch FE

	Model 1*	Model 2
DV	IRR	IRR
$\tilde{A}_{jo}$	-0.537***	-0.396**
	(0.152)	(0.158)
$\widetilde{D}_{j,o-1}$	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

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

*Note that we show the result of Model 1 in Table 4 in the first column.

Table WA5: Delinquency of Existing Loans with Branch FE

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

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

*Note that we show the result of Model 2 in Table 4 in the first column.

Table WA6: Instrumental Variable Regression - First Stage

DV	Amount IV	Duration IV
$\tilde{A}_{jo}$	0.013** (0.006)	0.082*** (0.025)
$\widetilde{D}_{j,o-1}$	-0.041* (0.022)	0.034 (0.089)
$Transfer_{jo}$	0.002 (0.008)	0.0997*** (0.0357)
Loan Amount	0.27*** (0.012)	1.86*** (0.011)
Duration	0.12*** (0.00075)	0.144*** (0.012)
Intercept	0.051 (0.033)	4.10*** (0.213)
Loan Characteristics	Yes	Yes
Salesperson FE Period FE	No Yes	Yes Yes
F-value	1474.87	130.78
N	89,860	89,860

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

Table WA7. IRR of Newly Originated Loans with Instrumental Variables

	Model 1	Model 2
DV	IRR(IV)	IRR (IV)
Instrument Variable	Average Amount	Average Duration
$\tilde{A}_{jo}$	-0.647*** (0.149)	-0.705*** (0.167)
$\widetilde{D}_{j,o-1}$	0.876* (0.528)	0.984* (0.567)
$Transfer_{jo}$	1.901*** (0.189)	1.795*** (0.232)
Rating 2	3.990*** (0.670)	5.473*** (0.735)
Rating 3	13.27*** (0.719)	18.48*** (1.445)
Rating 4	21.6*** (0.779)	29.81*** (2.191)
Rating 5	26.5*** (0.816)	34.83*** (2.213)
Loan Amount	1.136 (1.038)	-2.962*** (0.967)
Duration	-0.179 (0.127)	1.820*** (0.518)
Interest Rate	0.652*** (0.0133)	0.598*** (0.0176)
Intercept	-11.55*** (0.810)	-20.42*** (2.839)
Salesperson FE Period FE	No Yes	Yes Yes
N	89,860	89,860

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

Table WA8. IRR of Newly Originated Loans with new Instrumental Variables

DV	IRR (IV)	IRR (IV)
Instrument Variable	Average Amount	Average Duration
$\tilde{A}_{jo}$	-1.095*** (0.257)	-0.655*** (0.160)
$\widetilde{D}_{j,o-1}$	1.555** (0.722)	0.848 (0.568)
$Transfer_{jo}$	1.703*** (0.284)	1.689*** (0.227)
Intercept	-17.65*** (1.865)	-23.96*** (1.842)
Loan Characteristics	Yes	Yes
Salesperson FE Period FE	Yes Yes	Yes Yes
First Stage F-value	78.11	127.45
N	89,860	89,860

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

Table WA9. IRR of New Loans with Interaction between Transfer and Incentive States

	Model 1
DV	IRR
$\tilde{A}_{jo}$	-0.717*** (0.168)
$\tilde{A}_{jo} * Transfer_{jo}$	0.986*** (0.379)
$\widetilde{D}_{j,o-1}$	0.901* (0.535)
$Transfer_{jo}$	18.23*** (1.563)
Intercept	-13.91*** (1.267)
Loan Characteristics and Interactions with $Transfer_{jo}$	Yes
Salesperson, Period FE	Yes
N	89,993

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

Table WA10. IRR of Newly Originated Loans (Learning)

DV	IRR	IRR	IRR
		Positive $\tilde{A}_{jo}$	Negative $\tilde{A}_{jo}$
$\tilde{A}_{jo}$		-1.285** (0.544)	0.287 (0.334)
$Positive\ \tilde{A}_{jo}$	-0.514*** (0.134)		
$\widetilde{D}_{j,o-1}$	1.076** (0.537)	1.936** (0.810)	1.029* (0.557)
$Transfer_{jo}$	1.99*** (0.216)	3.018*** (0.352)	1.554*** (0.293)
Intercept	-10.60*** (1.231)	-9.56*** (1.851)	-10.96*** (1.637)
Loan Characteristics	Yes	Yes	Yes
Salesperson FE Period FE	Yes Yes	Yes Yes	No No
N	89,993	49,489	40,504

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

Table WA11. IRR of Newly Originated Loans (Learning)

DV	IRR
$\tilde{A}_{jo}$	-0.44*** (0.157)
$\widetilde{D}_{j,o-1}$	1.029* (0.557)
$Transfer_{jo}$	1.942*** (0.226)
Tenure	22.50*** (0.362)
Intercept	-251.6*** (4.249)
Loan Characteristics	Yes
Salesperson FE Period FE	Yes Yes
N	84,152

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

Table WA12. IRR of Newly Originated Loans (Learning about a region)

DV	IRR	IRR	IRR
$\tilde{A}_{jo}$	-0.321 (0.255)	-0.323 (0.255)	-0.295* (0.173)
$\tilde{A}_{jo}$* (Quarter = 2)	-0.684* (0.404)	-0.574 (0.407)	
$\tilde{A}_{jo}$* (Quarter > 2)	-0.107 (0.338)	-0.0920 (0.339)	
$\widetilde{D}_{j,o-1}$	3.439*** (0.880)	3.391*** (0.880)	0.986 (0.638)
$\widetilde{D}_{j,o-1}$* (Quarter = 2)	-4.799*** (1.459)	-4.766*** (1.460)	
$\widetilde{D}_{j,o-1}$* (Quarter > 2)	-3.204** (1.311)	-3.219** (1.311)	
$Transfer_{jo}$	2.025*** (0.217)	3.157*** (0.580)	2.328*** (0.243)
($Transfer_{jo}$= 0) * (Quarter = 2)		1.061*** (0.234)	
($Transfer_{jo}$= 0) * (Quarter > 2)		1.234*** (0.231)	
($Transfer_{jo}$= 1) * (Quarter = 2)		-0.518 (0.579)	
($Transfer_{jo}$= 1) * (Quarter > 2)		-0.791 (1.064)	
Intercept	-11.06*** (1.233)	-11.84*** (1.242)	-13.53*** (2.464)
Loan Characteristics	Yes	Yes	Yes
Salesperson FE Period FE	Yes Yes	Yes Yes	No No
Salesperson FE * Quarter FE	No	No	Yes
N	89,993	89,993	89,993

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