

When Salespeople Manage Customer Relationships: Multidimensional Incentives and Private Information

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Abstract

At many firms, incentivized salespeople with private information about customers are responsible for customer relationship management. Although incentives motivate sales performance, private information can induce moral hazard by salespeople to gain compensation at the expense of the firm. The authors investigate the sales performance–moral hazard trade-off 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, the authors 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, the adverse selection effect of acquisition incentives overwhelms the sales-enhancing effects, clarifying the importance of multidimensional incentives for customer relationship management. Reducing private information (through job transfers) hurts customer maintenance but has greater impact on productivity by moderating adverse selection at acquisition. This article 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

sales force compensation, customer relationship management, private information, adverse selection, moral hazard

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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., Gupta and Lehmann 2005; Li, Sun, and Montgomery 2011; Zhang, Netzer, and Ansari 2014), but has 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 balance sales from both new customer acquisition and existing customer retention and maintenance. However, typical compensation plans that have been studied in the literature (e.g., Chung, Steenburgh, and Sudhir 2013; Misra and Nair 2011; Schöttner 2016) are based on only a unidimensional measure of performance, such as total revenues, which do not decompose revenues that arise from new customers versus from maintenance of

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

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existing customers—the core of CRM concepts of customer acquisition and retention.²

Second, salespeople can have private information on customers, beyond the publicly available information that is known to the firm, through their relationships with customers. The private information can help the firm improve 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.

The issue of multidimensional sales force compensation in CRM settings is widely addressed in practice. According to a survey of sales compensation practices conducted by World-atWork (2016), a nonprofit human resources association of 154 of its U.S., Canadian, and international member organizations (covering public and privately held firms of various sizes across a range of industries), over 86% of organizations use more than one performance measure for sales force compensation. Figure 12 of the survey report shows that firms not only use a variety of metrics in determining compensation but also separate new and existing account revenues, account retention and expansion, customer satisfaction, and so on, indicating that they appreciate and incorporate the principles of CRM (by distinguishing and combining customer acquisition, retention, and growth performance metrics) in sales force compensation.

Our goal is to investigate the sales performance–moral hazard trade-off among salespeople in the use of managerial levers related to multidimensional incentives and private information when salespeople manage customer relationships. First, the multidimensional incentive scheme rewards salespeople on the basis of their joint performance on the acquisition and maintenance dimensions. Although acquisition metrics motivate salespeople to bring in sales through new customers, they also incentivize salespeople 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. Thus, 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 (through ongoing purchases/subscriptions, loan repayments, etc.). But beyond this direct effect, they can also moderate the moral hazard by indirectly incentivizing forward-looking salespeople to, *ex ante*, avoid acquiring 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 run, thus ameliorating the potential customer adverse selection motivation arising from acquisition incentives.

While the previous discussion shows that the effects of acquisition and maintenance metrics in isolation are intuitive, 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 salespeople 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. This result is insightful in that, theoretically, maintenance incentives not only can ameliorate adverse selection but can 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.

We consider a lever that a firm can use to control the level of private information salespeople have, 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 Although 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 dominates when there is a transfer is an empirical question.⁵

² A natural question is whether one could use aggregate CLV of a salesperson's acquired customers in a period as a unidimensional metric to determine incentives. Two practical challenges arise. First, CLV requires forecasting future customer revenues, but incentive contracts based on forecasts are often infeasible. Furthermore, 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 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 to receive loan acquisition bonuses because 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 business-to-business finance sector. France, Germany, and the United States, for example, mandate rotation of audit partners across clients. See the 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.

The discussion on how private information and multidimensional incentives interact to produce a sales performance–moral hazard trade-off makes clear that the effects of multidimensional incentives and private information on customer selection, maintenance, and overall productivity in CRM settings need empirical investigation. Accordingly, we address the following research questions relevant to sales force management in CRM settings:

1. Do salespeople have private customer information?
2. Do acquisition incentives affect acquired customers' unobservable quality, and if so, do they lead to advantageous or adverse customer selection?
3. Do maintenance incentives improve customer maintenance? How do they affect 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 trade-offs in terms of acquisition, maintenance efficiency, and selection effects?

Answering these questions poses several challenges. First, one needs matched panel data on sales force incentives/performance and customer relationships over time. This is typically difficult to obtain, as such data tend to reside separately within different functions of a firm. Specifically, the sales incentive and performance data reside within human resource/sales functions, 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 its loan officers (salespeople) with the loan acquisition and repayment behavior of its customers.

Second, detecting private information is challenging due to its intrinsic unobservability. Our primary identification strategy leverages the idea that, conditional on public information, sales force performance metrics under the incentive scheme should not *directly* affect future consumer repayment behavior and profitability of new customers but do so only *indirectly* through salespeople's efforts, as customers do not observe the metrics. Empirically, we test whether there is a systematic relationship between the salesperson's performance metrics, on which compensation is based, and the internal rate of return (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 its salespeople, severing past relationships and private information about its customers. The policy is designed to be random and unpredictable so that salespeople

cannot indulge in strategic behavior just prior to a transfer.⁶ The transfer policy enables 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 adverse selection because forward-looking salespeople anticipate the future consequences of 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 when the relationships between the salesperson and borrowers is severed. Thus, the periodic destruction of private information through transfers is a useful managerial lever in this setting.

The rest of the article is organized as follows. First, we discuss how this research is related to previous literature. Second, 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 discuss the key findings. Finally, we conclude and provide future research directions.

Relationship to the Literature

This article contributes to multiple literature streams in marketing and economics. As we discussed previously, the CRM literature has not addressed organizational issues of implementing CRM through an incentivized sales force, and this

⁶ Hertzberg, Liberti, and Paravisini (2010) find that loan officers are more likely to make negative reports on borrowers' ability to repay when they anticipate a transfer. 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.

Table 1. Previous Literature on Sales Force Compensation.

Research	Transaction/ Relationship	Performance Metric Uni/Multidimensional	Salesperson Moral Hazard (Hidden Action)	Firm/Agent Misalignment as Performance Metric Not Weighted by Observables
Oyer (1998)	Transactional (sales)	Unidimensional: Annual revenue targets	The author finds evidence that sales timing shifts to reach quota	N.A.
Misra and Nair (2011), Kishore et al. (2013)	Transactional	Unidimensional: Quarterly revenue targets with ratcheting	The authors find evidence that sales timing shifts to reach quota	N.A.
Chung, Steenburgh, and Sudhir (2013)	Transactional	Unidimensional: Quarterly and annual revenue targets with nonratcheting quotas	The authors find evidence that sales timing shifts to reach quota, but this can be minimized through overachievement commission and nonratcheting quotas	N.A.
Larkin (2014)	Transactional	Unidimensional: Annual revenues	None	Misalignment: Salespeople discount prices because 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	The authors find evidence that effort timing shifts based on distance to quota	Reduce misalignment <i>within</i> periods by weighting on the basis of observable job difficulty
The current research	Relationship (distinguish new and existing customers)	Multidimensional: Function of monthly loan acquisition and loan repayment	Due to salesperson private information about customers <ul style="list-style-type: none"> • Advantageous/adverse customer selection? • Customer maintenance? 	Reduce misalignment across periods: Future maintenance concerns discourage easier, low-quality (low credit rating) customer acquisition

Notes: N.A. = not applicable.

article addresses that important omission, given the ubiquity of sales force–driven CRM across many industries.⁸

Our primary contribution is to the empirical literature on sales force compensation, which we summarize with the four columns in Table 1. First, the existing empirical sales force compensation literature (e.g., Chung, Steenburgh, and Sudhir 2013; Misra and Nair 2011) either focuses on the situation in which one-shot transactions generate sales or ignores the distinction between sales that arise from new customers and those with existing relationships. This article adds to the literature by examining the important case in which ongoing customer relationships matter, and therefore it is important to distinguish between sales from new customers versus sales from customers with whom there is already a relationship. Second, existing empirical sales force compensation research has studied unidimensional performance metrics. Although there have been a large number of empirical studies in the fields of education and health on the multitasking agency problem (e.g., Feng Lu 2012; Neal and Schanzenbach 2010) since the seminal theoretical work by Holmstrom and Milgrom (1991), to the best of our knowledge, ours is the first empirical article on sales force

compensation that studies a multidimensional compensation scheme.

Third, our article introduces the issue of private information as a source of salesperson moral hazard. Existing empirical research has considered 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 (e.g., Chevalier and Ellison 1997; Steenburgh 2008). In contrast, we focus on salesperson moral hazard arising from the existence of private information about 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 article considers potential misalignments between a firm and its sales force 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

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

workers is eliminated because the firm's performance metric puts greater weight on performance of difficult jobs. In these works, at least conceptually, it is possible to address misalignment that results from differences in true productivity based on observables by appropriately reweighting contemporaneous variables without concerns for intertemporal effects. In our article, the firm faces a misalignment issue due to unobservable (or noncontractible) 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 article is also related to the literature on social capital in organizations (Sorenson and Rogan 2014). As noted previously, salespeople's private information 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 business-to-business setting and find that customer reassignment to different types of salespeople leads to customer churn with 13.2%–17.6% losses in annual sales for the firm; however, they do 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 his or her interactions. These works suggest that the salesperson–customer relationship is valuable to the firm for customer maintenance. Herein, we show that although this intangible asset (i.e., private ties that constitute relational contracts) is useful to the 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 (Canales and Greenberg 2015; Fisman, Paravisini, and Vig 2011).

Methodologically, this study contributes to a growing body of 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 that in our empirical setting, loan default is a form of customer moral hazard. It is challenging to identify the existence of private information and quantify its effects because of its intrinsic unobservability. Chiappori and Salanie (2000) initiated this stream of literature and propose a positive correlation test to detect asymmetric information in the car insurance market. Subsequent studies have tested for asymmetric information in health insurance by obtaining access to additional information (e.g., preexisting conditions) that insurance companies cannot lawfully use (Finkelstein and McGarry 2006; Finkelstein and Poterba 2004) to find whether this information explains the type of insurance plans people choose as well as their 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

observing only ex post customer behaviors.⁹ Prior studies have addressed the issue through a randomized controlled experiment with contract terms (Karlan and Zinman 2009) or by exploiting policy changes (Dobbie and Skiba 2013). Jeziorski, Krasnokutskaya, and Ceccarini (2017) use the specific institutional rules of the Portuguese auto insurance market to address adverse selection and moral hazard. Our article introduces a new identification strategy that exploits "supply-side" variation in 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. We subsequently explain the data used in our empirical analysis.

Institutional Details

Our empirical application is in the context of a microfinance institution 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 six months), and high delinquency probability (average of approximately 25.4%), as is common for microcredit institutions in emerging markets (for more discussion on microcredit loans in emerging markets, see, e.g., Sengupta and Aubuchon [2008]).

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. Because salespeople have a great deal of discretion to approve a loan in our setting, they do not need to have a borrower take further actions if they want 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

⁹ The relationship between loan officers' incentives and their screening/monitoring behaviors has been studied in finance (Agarwal and Ben-David 2014; Cole, Kanz, and Klapper 2015; Heider and Inderst 2012; Hertzberg, Liberti, and Paravisini 2010). These works 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.

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 that hurts the firm.¹²

The salesperson's compensation in the bank we study has two parts: salary and bonus. The salary is determined solely 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 $A_{jt} = N_{jt}/Q_{jt}^A$, where N_{jt} is the amount of new loans acquired by officer 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 ($M_{jt} = R_{jt}/LV_{jt}$ 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). Thus, $D_{jt} = 1 - M_{jt}$ 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 the future negative effects 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 2017). Transferred salespeople take over and monitor the loans acquired by their predecessors who left the branch. The transferred salesperson's maintenance index does not depend on the loans she 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 microfinance institution 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. This allows us to treat transfers as an exogenous shock to salesperson private information.

Data

Our panel data include monthly sales force 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, 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) as well as their score on the acquisition and maintenance benchmarks, which determined their bonus.

Table 2 reports summary statistics of loan characteristics and bonus points. The average loan size is 9,192 pesos (approximately US\$690 in 2009), with an average loan term of six 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 .75 and maintenance points (M) is .85; the average of the overall bonus multiplier ($A \times M$) is .59 of the salary. Although we have significant missing values for the salary information, the average base salary is 4,050 Mexican pesos (US\$313). Finally, the average number of transfers is .37, with a maximum of three transfers over the 14 months we observe.

¹¹ Drawing on interviews, Canales (2013) notes that salespeople do not completely trust observables and tend to act on the basis of private information. We quote from two interviews:

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.

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

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

Table 2. Summary Statistics.

	Mean	SD	Min	Max
Loan Characteristics				
Amount (pesos)	9,192	8,956	700	55,000
Annual interest rate (%)	87.21	8.81	42	100.29
Duration (months)	6.27	3.89	1	33
Delinquency (%)	25.42			
Sales Force Incentives and Transfer				
By Salesperson-Period				
Acquisition point (A)	.75	.45	0	3.188
Maintenance point (M)	.85	.23	0	1.25
By Salesperson				
A × M	.59	.3		
No. of transfers	.37	.55	0	3

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, and 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 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 3 further explores the relationship between credit rating and loan characteristics. We find that 71% of the loans are given to those with a creditworthiness rating of 5, and 18% to those with creditworthiness rating of 4. Only 11% of loans are given to those with creditworthiness 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 in which all first-time clients start at the highest rate that gradually lowers 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 (Table 4). 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 performance up to three months before transfer, or with other officer characteristics, such as education level, marital status, relationship type (Canales 2013; Canales and Greenberg 2015), or position within the firm.

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 a formal structure to clarify the intuition underlying the arguments regarding how private information affects the pool of accepted customers and monitoring intensity and to shed light on 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), which 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 do).

Customer Primitives

Prospective customers arrive periodically with loan requests to a salesperson. The salesperson decides whether to offer a loan to each prospective customer given the salesperson's 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., $0 \leq p_L < p_H$). Furthermore, 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 that 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, and A and M the acquisition and maintenance metrics of performance. Consistent with our empirical setting, we use the following bonus function: $B = S \times A \times M$, 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 a

¹⁴ This is because observably high-type customers have more outside options due to greater competition for their business (for such evidence in car insurance market, see Jeziorski et al. [2017]).

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

Table 3. 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	.65	.36	88.67	9.83	10.76	6.38
2	3,089	53.36	39.46	.59	.38	86.71	9.58	10.84	6.89
3	6,754	66.98	35.63	.46	.38	88.1	8.46	8.43	4.41
4	23,768	79.16	23.96	.25	.3	86.27	7.25	6.13	3.77
5	91,744	87.28	19.66	.14	.22	87.58	9.13	5.84	3.38

Table 4. Randomness of Transfer Policy

DV	Model 1 Transfer _t	Model 2 Transfer _t	Model 3 Transfer _t	Model 4 Transfer _t	Model 5 Transfer _t	Model 6 Transfer _t	Model 7 Transfer _t
A _{t-1}	-.251 (.203)		-.294 (.206)				-.0195 (1.199)
M _{t-1}		.342 (.387)	.429 (.406)				-1.771 (2.916)
Tenure				-.00199 (.00139)			.00960 (.00850)
Female					.368 (.241)		1.645 (1.047)
Time since last transfer						.151 (.0957)	.357 (.282)
Intercept	-2.897*** (.304)	-3.505*** (.452)	-3.218*** (.439)	-2.716*** (.152)	-3.440*** (.182)	-4.284*** (.486)	-6.338* (3.493)
Period fixed effects	Yes	Yes	Yes	No	No	No	Yes
N	2,603	2,646	2,590	3,224	1,947	696	150

Notes: DV = dependent variable. We run logistic regression (DV: Transfer, Indicator 1) if an officer is new to the branch at period t).

certain type is inversely proportional to the customer's rate of arrival. Thus, the cost of effort for acquiring a high- and low-type customer is $1/\lambda_H$ and $1/\lambda_L$, respectively. Therefore, if a salesperson acquires n_H high- and n_L low-type customers, the acquisition effort is given by $e_a = (n_H/\lambda_H) + (n_L/\lambda_L)$. 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, 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., $c(e) = (c/2)(e_a + e_m)^2$).

A key characteristic of the bonus scheme is that the maintenance metric (the fraction of delinquent loans in the salesperson's loan portfolio) induces intertemporal forward-looking behavior by salespeople who anticipate how the mix of customers they acquire and the maintenance efforts they incur to avoid delinquency in the present will affect their future compensation through their 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 nontrivial.

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 that $V_D = 0$.

Salesperson Acquisition and Maintenance Choices

Next, we 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 nondelinquent loans in the portfolio are kh , kd , and $k(1 - h - d)$, 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). However, the salesperson with private customer information can identify the borrower's type

and acquire or maintain loans differentially by type. Given that all borrowers are otherwise identical, a salesperson’s choice in the acquisition stage is the fraction of arriving prospective borrowers to accept by borrower type. We denote the fraction as α_H for high types 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 monitor only low types who are not delinquent, as high types always repay and delinquent loans never repay. For a monitoring intensity of p , as described previously, the repayment probability of the low type is $p_L = p$.

Next, 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 $(\lambda\alpha_H + \alpha_L) \times [h + (1 - h - d)p]$. 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 $(c/2)e^2$.

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:

$$U(\alpha_H, \alpha_L, p) = (\lambda_H\alpha_H + \alpha_L) \times [h + (1 - h - d)p] - \frac{c}{2}(\alpha_H + \alpha_L + mp)^2 + \{(\lambda_H\alpha_H + kh)V_H + [\alpha_L + k(1 - h - d)p]V_L\};$$

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^* . Next, we state the key propositions from our analysis. To help shed light on the effects of private information, we begin with a benchmark result on customer acquisition for the symmetric information case, in which neither the salesperson nor the 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 is equal (i.e. $\alpha_L^*/\alpha_H^* = 1$). The ratio of number of low to high types among newly acquired customers $\alpha_L^*/\lambda\alpha_H^*$ equals the ratio of the arrival rates of the two types ($1/\lambda$), 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.

P₁: With regard to customer selection in acquisition with salesperson private information:

- a. As the 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 $\alpha_L^*/\lambda\alpha_H^*$ decreases until it reaches zero, at which point, only high types are acquired.
- b. 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 ($\alpha_L^*/\lambda\alpha_H^*$) is lower than the symmetric case (i.e., $\alpha_L^*/\lambda\alpha_H^* < 1/\lambda$); that is, there is advantageous selection relative to the symmetric case. In contrast, below d^* , there is adverse selection in new customer acquisition (i.e., $\alpha_L^*/\lambda\alpha_H^* > 1/\lambda$).

For the proof of P₁, see the Appendix.

Figure 1 illustrates the proposition with a numerical example for the case of $\lambda = .4, k = .45, c = .65, m = .01, V_L = .25, V_H = 1.625$, and $h = .6$. Figure 1, Panel A, shows that the share of low types decreases and that of high types increases as d increases. In Figure 1, Panel B, 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 ($1/\lambda$), indicating the shift from adverse selection to advantageous selection.

P₁ states that when salespeople have higher maintenance pressure (higher share of delinquent loans in portfolio), they bring in 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.

P₂: With regard to ex post (after acquisition) maintenance effort and loan delinquency: as the share of delinquent loans d in the salesperson’s portfolio increases, his or her maintenance effort increases. The resulting probability of loan defaults falls monotonically with d (i.e., $\partial p^*/\partial d > 0$).

For the proof of P₂, see the Appendix.

P₂ 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 previous numerical example, Figure 1, Panel C, shows that monitoring effort p increases in d .

Empirical Analysis

Identification Strategy

Given that 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) that transfers exogenously change the level of salespeople’s private information about customers.

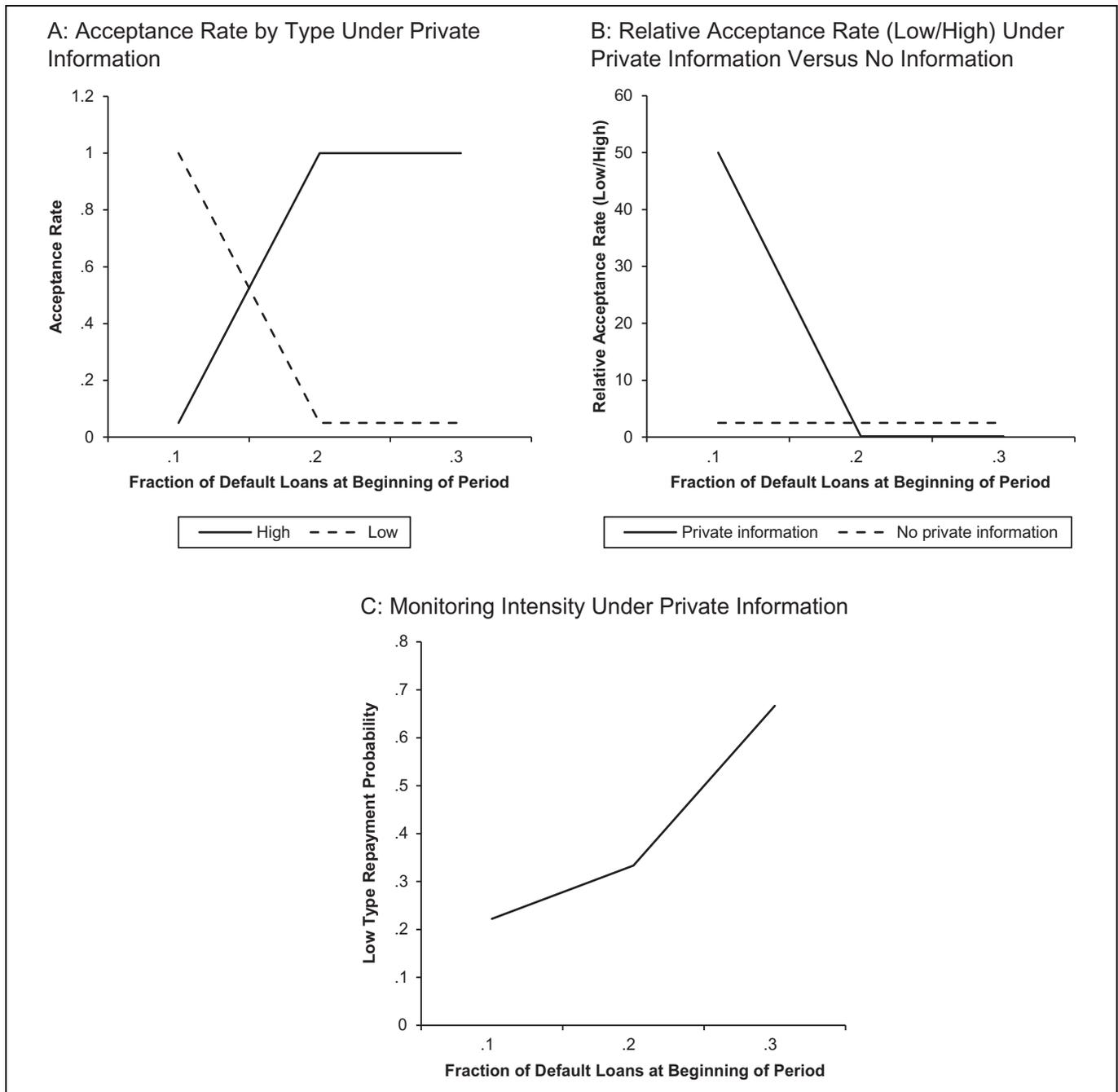


Figure I. Propositions from analytical model with a numerical example
 Notes: Optimal behavior under $\lambda = .4$, $k = .45$, $c = .65$, $m = .01$, $V_L = .25$, $V_H = 1.625$, and $h = .6$.

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 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. A 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

increases/reduces 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 the managerial levers of acquisition/maintenance incentives and transfers. This enables us to test for the existence of private information and empirically assess how multidimensional incentives and transfers affect 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:

$$\begin{aligned} \text{IRR}_{ij_o} = & \alpha_1 + \beta_1 \tilde{A}_{j_o} + \beta_2 \tilde{D}_{j,o-1} + \gamma_1 \text{Transfer}_{j_o} \\ & + \gamma_2 X_i + \mu_j + \phi_o + \epsilon_{ij_o}. \end{aligned} \quad (1)$$

In Equation 1, IRR_{ij_o} is the internal rate of return of loan i , originated by officer j at time o . IRR_{ij_o} measures loan performance realized after the loan cycle. To eliminate the effects of cross-sectional variation across salespeople and focus on intrasalesperson states, we demean acquisition performance (A_{j_o}) by salesperson average across all periods to obtain \tilde{A}_{j_o} . 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 \tilde{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 $\tilde{D}_{j,o-1}$ in the regression. The dummy variable Transfer_{j_o} 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, interest rate, and the number of months since origination. The model also includes loan officer fixed effects to control for unobserved heterogeneity in salespeople, such as risk aversion, leniency, or effect of quotas. Finally, the model has time fixed

effects ϕ_o to capture any macrolevel 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 coefficient 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 a result of the salesperson seeking 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). Finally, 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, because we control for their incentive states \tilde{A}_{j_o} and $\tilde{D}_{j,o-1}$ in the specification.

Table 5 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 .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 sales force, that higher acquisition performance accentuates adverse selection and maintenance pressure and transfers mitigate adverse selection. We also 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. These results remain robust—all of the specifications support the hypothesis that the marginal quality of the loan suffers from 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 increases. Smaller loan amounts, longer durations, and higher interest rates are associated with lower profitability.

Finally, in an unreported specification, we test whether 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, in support of the hypothesis.

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

Table 5. Internal Rate of Return (IRR) of Newly Originated Loans.

DV	Model 1	Model 2	Model 3
	IRR	IRR	IRR
\tilde{A}_{jo}	-.537*** (.152)	-.540*** (.152)	-.645*** (.159)
$\tilde{D}_{j,o-1}$	1.070** (.538)	1.059** (.538)	.970* (.567)
$\tilde{A}_{jo} * \tilde{D}_{j,o-1}$		-.556 (1.382)	
$(\tilde{A}_{jo})^2$			-.556** (.244)
$(\tilde{D}_{j,o-1})^2$			1.037 (1.851)
Transfer _{jo}	1.987*** (.216)	1.984*** (.216)	1.988*** (.216)
Rating 2	3.991*** (.598)	3.991*** (.598)	3.995*** (.598)
Rating 3	13.33*** (.476)	13.33*** (.476)	13.33*** (.476)
Rating 4	21.74*** (.420)	21.74*** (.420)	21.75*** (.420)
Rating 5	26.66*** (.404)	26.66*** (.404)	26.66*** (.404)
Loan amount	.630*** (.0790)	.630*** (.0790)	.629*** (.0790)
Duration	-.108*** (.0202)	-.108*** (.0202)	-.108*** (.0202)
Interest rate	.657*** (.00703)	.657*** (.00703)	.657*** (.00703)
Intercept	-10.95*** (1.231)	-10.97*** (1.232)	-10.87*** (1.233)
Salesperson, period fixed effects	Yes	Yes	Yes
N	89,993	89,993	89,993

* $p < .1$.** $p < .05$.*** $p < .01$.

Maintenance: Ex Post Loan Repayment

Next, we investigate how maintenance pressure and transfers affect 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 because they have less information to target their maintenance effort, where they are most needed. Thus, we run the following regression.

$$\begin{aligned} \text{Delinquency}_{ijt} &= \alpha_1 + \beta_1 \tilde{A}_{jt} + \beta_2 \tilde{D}_{j,t-1} + \gamma_1 \text{Transfer}_{jt} \\ \text{Bad}_{it-1} &(\alpha_2 + \beta_3 \tilde{A}_{jt} + \beta_4 \tilde{D}_{j,t-1} + \gamma_2 \text{Transfer}_{jt}) \\ &+ \gamma_3 X_{it} + \mu_j + \phi_t + \epsilon_{ijt}. \end{aligned} \quad (2)$$

Note that Equations 1 and 2 examine salespeople's behavior at different stages (acquisition stage is 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., $\text{Bad}_{it-1} = 1$) and those that are repaid on time in period $t - 1$ (i.e., $\text{Bad}_{it-1} = 0$). We do so because a salesperson's monitoring may have greater impact on loans that are not currently delinquent (i.e., $\text{Bad}_{it-1} = 0$), 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 resulting private information do help target efforts on the right borrowers and ensure repayment.

Table 6 reports the estimates. 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 $\tilde{D}_{j,t-1}$ 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 .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 $\text{Bad}_{i,t-1}$ suggests that loans that are delinquent are more likely to remain so. Thus, under high maintenance pressure, officers are less likely

Table 6. Delinquency of Existing Loans.

DV	Model 1	Model 2	Model 3
	Delay	Delay	Delay
$\tilde{D}_{j,t-1}$	-.0201*** (.00763)	-.0203*** (.00764)	-.0203*** (.00778)
Transfer _{jt}	.00448* (.00257)	.00442* (.00257)	.00442* (.00257)
Bad _{i,t-1}	.470*** (.00198)	.470*** (.00198)	.470*** (.00198)
Bad _{i,t-1} * $\tilde{D}_{j,t-1}$.0954*** (.0128)	.0957*** (.0128)	.0957*** (.0129)
Bad _{i,t-1} * Transfer _{jt}	-.00403 (.00390)	-.00376 (.00390)	-.00377 (.00391)
\tilde{A}_{jt}		-.00440** (.00178)	-.00441** (.00180)
Bad _{i,t-1} × \tilde{A}_{jt}		.000994 (.00321)	.000999 (.00322)
\tilde{A}_{jt} × $\tilde{D}_{j,t-1}$			-.000431 (.0169)
Bad _{i,t-1} × \tilde{A}_{jt} × $\tilde{D}_{j,t-1}$.000603 (.0300)
Rating 2	-.00468 (.00415)	-.00468 (.00415)	-.00468 (.00415)
Rating 3	-.0720*** (.00351)	-.0720*** (.00351)	-.0720*** (.00351)
Rating 4	-.165*** (.00314)	-.165*** (.00315)	-.165*** (.00315)
Rating 5	-.253*** (.00301)	-.253*** (.00301)	-.253*** (.00301)
Loan amount	-.00482*** (.000718)	-.00483*** (.000718)	-.00483*** (.000718)
Duration	.00162*** (.000180)	.00163*** (.000180)	.00163*** (.000180)
Interest rate	.00212*** (.0000686)	.00212*** (.0000686)	.00212*** (.0000686)
Age of loan	.0113*** (.000299)	.0113*** (.000299)	.0113*** (.000299)
Intercept	.126*** (.0112)	.126*** (.0112)	.126*** (.0112)
Salesperson, period fixed effects	Yes	Yes	Yes
N	278,943	278,943	278,943

*p < .1.
 **p < .05.
 ***p < .01.

to monitor such loans and more likely to focus on loans currently in good standing. The positive coefficient of $Bad_{i,t-1} \times \tilde{D}_{j,t-1}$ 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 summary, 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 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 (NPV) 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 improve customer repayment. Transfers that 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 of the incentives and transfers on overall sales force productivity? To answer this, we examine whether the sales-enhancing effect of the incentive levers (e.g., Chung, Steenburgh, and Sudhir 2013) 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 salesperson-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:

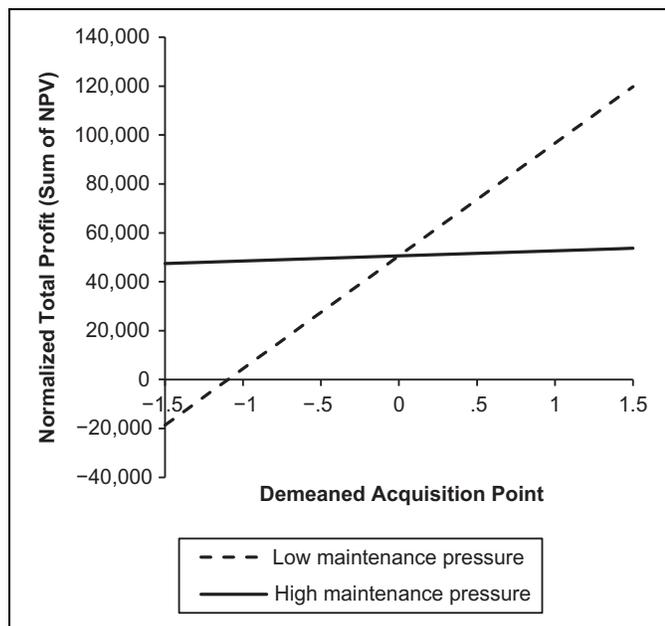
$$NPV_{jo} = \alpha_1 + \beta_1 \tilde{A}_{jo} + \beta_2 \tilde{D}_{j,o-1} + \beta_3 (\tilde{A}_{jo} \times \tilde{D}_{j,o-1}) + \gamma_1 Transfer_{jo} + \gamma_2 X_i + \mu_j + \phi_o + \epsilon_{ijo} \quad (3)$$

The dependent variable NPV_{jo} represents the sum of the net present value of new loans (in thousands of pesos) 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.

¹⁷ The total NPV metric is similar in spirit to the salesperson lifetime value metric in Kumar, Sunder, and Leone (2013) at the salesperson-month level but with ex post known (as opposed to forecast) values of future customer cash flows.

Table 7. Total NPV of Originated Loans by Salesperson by Month.

DV	Model 1	Model 2
	NPV _{jo}	NPV _{jo}
\tilde{A}_{jo}	2.390*** (.264)	2.410*** (.264)
$\tilde{D}_{j,o-1}$	-.205 (.924)	-.000635 (.930)
$\tilde{A}_{jo} \times \tilde{D}_{j,o-1}$		4.403* (.2431)
Transfer _{jo}	.928*** (.323)	.941*** (.323)
Intercept	4.957*** (1.885)	5.058*** (1.885)
Salesperson fixed effects	Yes	Yes
Period fixed effects	Yes	Yes
N	3,403	3,403

* $p < .1$.** $p < .05$.*** $p < .01$.**Figure 2.** Profit under high versus low maintenance pressure.

Notes: Profit is in Mexican pesos.

Table 7 reports the regression results. Model 1 is the base-line case, and the estimates show that β_1 is positive, β_2 is positive, γ_1 is 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 .5 points below average), the greater acquisition performance leads to a sharp increase in profits, but when the maintenance pressure is low (.5 points above 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.

Finally, the coefficient on transfers as per Model 2 show that a transfer leads to an NPV increase of 941 pesos during the month of transfer, taking into account the positive benefits of reducing adverse selection in customer acquisition and the negative costs of lower loan repayment. Given that the average NPV of loans per month generated is approximately 12,300 pesos, the net benefit for the bank from transfer is about 7.6% of its average salesperson productivity in that month. While the benefit may seem relatively small relative to the costs imposed on employees from transfers, we note that employee costs are relatively small given that, in our empirical setting, transfers here are merely territory shifts within a city. Furthermore, given the relatively thin net margins for this nonprofit, this improvement is indeed economically significant.

Managerial Implications

Our analytical approach and our findings about 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 sales force productivity in the presence of private information can be widely used. We note that although our application is in a setting of multidimensional incentives in which the sales force is responsible for both customer acquisition and retention, the acquisition and productivity regressions can also be used to measure adverse selection effects and net productivity effects (sales expansion–adverse selection trade-off) of incentives when sales forces are only incentivized for acquisition.

Next, we discuss how our findings provide guidance for sales force management. First, while managers understand 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 sales force moral hazard, the overall benefits from acquisition incentives can be negative because of adverse selection and lack of attention to retention. This suggests that sales management should evaluate the cost of sales force moral hazard and remedies more seriously, even when only acquisition incentives are offered. In particular, we highlight the role of transfers as way to “kill” private information to reduce salesperson moral hazard. Although 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–sales force 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 acquisition for firm value. Although weighting acquired customers by CLV is a possibility, it is often infeasible because (1) CLV requires forecasts of future retention and revenues, and it may not be feasible to tie incentives to forecasts, and (2) it is not possible to hold the salesperson responsible for future retention once payments have been made based on forecasts. Multidimensional incentives in which incentives balance current acquisition and future maintenance performance are an effective managerial solution in these settings without requiring future forecasts. We also note that such weighting may be appropriate when salespeople are responsible for multiple territories and products with different levels of difficulty in generating revenues/margins.

Finally, our findings have implications for job design in CRM settings. Firms implementing CRM often use a hunter–farmer model in which 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 article aims at addressing the challenges of the sales performance–moral hazard trade-off that arises when salespeople manage customer relationships. We consider the role of multidimensional incentives that are based on joint acquisition and maintenance metrics in the presence of private information. A stylized analytical model of salesperson behavior in CRM settings helps us understand how acquisition and maintenance jointly affect 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 affect 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 when firms use only acquisition performance incentives by estimating only the customer acquisition and productivity regressions. Methodologically, this article also introduces a new identification strategy to detect and disentangle the 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 research is a first step to address a rich set of 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. However, 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, and so on. Further research is needed on how firms should incentivize salespeople for such CRM-related metrics.

Second, substantive research on multidimensional incentives is still scarce. Although multidimensional incentives involve balancing short-term and long-term considerations with acquisition and maintenance incentives in our setting, 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. While frequent random transfers without much notice is feasible in our setting because the bank operates within only one metropolitan area (so salespeople can easily travel to any of the territories), such transfers may not be feasible in other settings. Yet, as we noted previously, Indian banks periodically (every two to three years) do transfer relatively highly paid branch managers to address the adverse selection situation. 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, although we find that transfers have a net benefit for the bank, Shi et al. (2017) find in the context of an electrical product retailer that customer–salesperson reassignment (equivalent to transfers) can lead to significant loss due to customer churn. However, Shi et al. do not consider the adverse selection issue. Future research should investigate how the relative importance of adverse selection versus efficiency from private information varies across industries and how managers can balance these components.

Finally, our results should motivate more research on salesperson job design in CRM settings. In bank and insurance

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

settings, salespeople are responsible for both customer acquisition and maintenance, but 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). These questions of job design and compensation design are explored in depth in Kim, Sudhir, and Uetake (2019) through a structural model of multitasking behavior in the presence of perfect information.

Appendix

Details on Compensation Plan

We describe the specifics of how acquisition and maintenance points are calculated for the purposes of compensation. Table

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 of 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.

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.

$$\alpha_H^* = \frac{1}{c(1-h-d)^2(1-\lambda)^2} \left\{ (1-h-d)^2 \{V_H\lambda + V_L[ck(1-\lambda) - \lambda]\} - cm \left[h^2(1-\lambda) + [c + 2(1-d)]V_H\lambda - cV_L - (1-d)(1+\lambda)V_L - h \begin{matrix} \left[1-d + c(1-\lambda) - \lambda(1-d) + 2V_H\lambda \right] \\ \left[-V_L(1+\lambda) \right] \end{matrix} \right] + c^2m^2[V_H\lambda - V_L - h(1-\lambda)] \right\},$$

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

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

Proof of P1. $\frac{\partial}{\partial d} \left(\frac{\alpha_H^*}{\lambda\alpha_L^*} \right) < 0$ when $d < \frac{(1-h)\lambda^2(V_H - V_L)^2 + c[V_H\lambda - V_L - h(1-\lambda)][V_H\lambda(1-m) + V_Lk(1-h)(1-\lambda) - \lambda(1-m)]}{c h k V_L(1-\lambda)^2 + \{V_H^2\lambda^2 - V_H\lambda V_L[ck(1-\lambda) + 2\lambda] - [\lambda^2 + ckV_L^2(1-\lambda)]\}}$

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

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

$$d < \frac{1}{2\lambda(1-\lambda)(V_H - V_L) + 4ckV_L(1-\lambda)} \{ 2\lambda(1-h)(1+\lambda)(V_H - V_L) + ckV_L\{4(1-h)(1-\lambda) + [h(1+\lambda^2) + (1+3\lambda)V_L - V_H\lambda(3+\lambda)]m\} + cm(m[8(V_H\lambda - V_L - h(1-\lambda))(V_H\lambda(1+\lambda) + V_L[2ck(1-\lambda) - \lambda(1+\lambda)] + (1-\lambda)\{V_H^2\lambda^2(1-\lambda) + h^2(1-\lambda)(1+\lambda)^2 - 2V_HV_L\lambda(1-\lambda - 8ck) - (1-\lambda + 16ck)V_L^2 + 2hV_L(1-\lambda)[V_H\lambda(1+\lambda) + (1+\lambda + 8ck)]\}^{1/2}) \}$$

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

Proof of P2. $\frac{\partial p^*}{\partial d} = \frac{\lambda(V_H+h)-(V_L+h)}{(1-\lambda)(1-h-d)^2} > 0$ since $\lambda(V_H + h) - (V_L + h) > 0$.

Table A1. Acquisition Target.

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

Table A2. Maintenance Point.

% Loan Amount in Good Standing	Points
0%–87.5%	0
87.6%–88.5%	.5
88.6%–90.0%	.6
90.1%–92.5%	.65
92.6%–93.0%	.7
93.1%–93.5%	.75
93.6%–94.0%	.8
94.1%–94.5%	.85
94.6%–96.0%	.9
96.1%–96.5%	1
96.6%–97.0%	1.05
97.1%–97.5%	1.08
97.6%–98.0%	1.1
98.1%–99.0%	1.15
99.1%–99.5%	1.2
99.6%–100%	1.25

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References

- Agarwal, Sumit and Itzhak Ben-David (2014), *Do Loan Officers' Incentives Lead to Lax Lending Standards?* New York: Mimeo.
- Canales, Rodrigo (2013), "Weaving Straw into Gold: Managing Organizational Tensions Between Standardization and Flexibility in Microfinance," *Organization Science*, 25 (1), 1–28.
- Canales, Rodrigo and Jason Greenberg (2015), "A Matter of (Relational) Style: Loan Officer Consistency and Exchange Continuity in Microfinance," *Management Science*, 62 (4), 1202–24.
- Chevalier, Judith and Glenn Ellison (1997), "Risk Taking by Mutual Funds as a Response to Incentives," *Journal of Political Economy*, 105 (6), 1167–200.
- Chiappori, Pierre-André and Bernard Salanie (2000), "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy*, 108 (1), 56–78.
- Chung, Doug J., Thomas Steenburgh, and K. Sudhir (2013), "Do Bonuses Enhance Sales Productivity? A Dynamic Structural Analysis of Bonus-Based Compensation Plans," *Marketing Science*, 33 (2), 165–87.
- Cole, Shawn, Martin Kanz, and Leora Klapper (2015), "Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers," *Journal of Finance*, 70 (2), 537–75.
- Copeland, Adam and Cyril Monnet (2009), "The Welfare Effects of Incentive Schemes," *Review of Economic Studies*, 76 (1), 93–113.
- Dobbie, Will and Paige Marta Skiba (2013), "Information Asymmetries in Consumer Credit Markets: Evidence from Payday Lending," *American Economic Journal: Applied Economics*, 5 (4), 256–82.
- Feng Lu, Susan (2012), "Multitasking, Information Disclosure, and Product Quality: Evidence from Nursing Homes," *Journal of Economics & Management Strategy*, 21 (3), 673–705.
- Finkelstein, Amy and Kathleen McGarry (2006), "Multiple Dimensions of Private Information: Evidence from the Long-Term Care Insurance Market," *American Economic Review*, 96 (4), 938–58.
- Finkelstein, Amy and James Poterba (2004), "Adverse Selection in Insurance Markets: Policyholder Evidence from the UK Annuity Market," *Journal of Political Economy*, 112 (1), 183–208.
- Fisman, Raymond, Daniel Paravisini, and Vikrant Vig (2011), "Social Proximity and Loan Outcomes: Evidence from an Indian Bank," working paper.
- Fisman, Raymond, Daniel Paravisini, and Vikrant Vig (2017), "Cultural Proximity and Loan Outcomes," *American Economic Review*, 107 (2), 457–92.
- Grossman, Sanford J. and Oliver D. Hart (1986), "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration," *Journal of Political Economy*, 94 (4), 691–719.

- Gupta, Sunil and Donald R. Lehmann (2005), *Managing Customers as Investments: The Strategic Value of Customers in The Long Run*. Upper Saddle River, NJ: Wharton School Publishing.
- Heider, Florian and Roman Inderst (2012), "Loan Prospecting," *Review of Financial Studies*, 25 (8), 2381–2415.
- Hertzberg, Andrew, Jose Liberti, and Daniel Paravisini (2010), "Information and Incentives Inside the Firm: Evidence from Loan Officer Rotation," *Journal of Finance*, 65 (3), 795–828.
- Holmstrom, Bengt and Paul Milgrom (1991), "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics, & Organization*, 7 (Special Issue), 24–52.
- Jain, Dipak and Siddhartha S. Singh (2002), "Customer Lifetime Value Research in Marketing: A Review and Future Directions," *Journal of Interactive Marketing*, 16 (2), 34–46.
- Jeziorski, Przemyslaw, Elena Krasnokutskaya, and Olivia Ceccarini (2017), "Adverse Selection and Moral Hazard in a Dynamic Model of Auto Insurance," (working paper), <http://sticerd.lse.ac.uk/semipapers/em23022017.pdf>.
- Karlan, Dean and Jonathan Zinman (2009), "Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment," *Econometrica*, 77 (6), 1993–2008.
- Kim, Minkyung, K. Sudhir, and Kosuke Uetake (2019), "A Structural Model of a Multi-Tasking Salesforce: Job Task Allocation and Incentive Plan Design," working paper, Yale School of Management, Yale University.
- Kishore, Sunil, Raghunath S. Rao, Om Narasimhan, and George John (2013), "Bonuses Versus Commissions: A Field Study," *Journal of Marketing Research*, 50 (3), 317–333.
- Kumar, V., Sarang Sunder, and Robert P. Leone (2013), "Measuring and Managing a Salesperson's Future Value to the Firm," *Journal of Marketing Research*, 51 (5), 591–608.
- Larkin, Ian (2014), "The Cost of High-Powered Incentives: Employee Gaming in Enterprise Software Sales," *Journal of Labor Economics*, 32 (2), 199–227.
- Li, Shibo, Baohong Sun, and Alan L. Montgomery (2011), "Cross-Selling the Right Product to the Right Customer at the Right Time," *Journal of Marketing Research*, 48 (4), 683–700.
- Misra, Sanjog and Harikesh S. Nair (2011), "A Structural Model of Sales-Force Compensation Dynamics: Estimation and Field Implementation," *Quantitative Marketing and Economics*, 9 (3), 211–57.
- Neal, Derek and Diane Whitmore Schanzenbach (2010), "Left Behind by Design: Proficiency Counts and Test-Based Accountability," *Review of Economics and Statistics*, 92 (2), 263–83.
- Oyer, Paul (1998), "Fiscal Year Ends and Nonlinear Incentive Contracts: The Effect on Business Seasonality," *Quarterly Journal of Economics*, 113 (1), 149–85.
- Palmatier, Robert W., Lisa K. Scheer, and Jan-Benedict E.M. Steenkamp (2007), "Customer Loyalty to Whom? Managing the Benefits and Risks of Salesperson-Owned Loyalty," *Journal of Marketing Research*, 44 (2), 185–99.
- Reinartz, Werner, Manfred Krafft, and Wayne D. Hoyer (2004), "The Customer Relationship Management Process: Its Measurement and Impact on Performance," *Journal of Marketing Research*, 41 (3), 293–305.
- Schöttner, Anja (2016), "Optimal Sales Force Compensation in Dynamic Settings: Commissions vs. Bonuses," *Management Science*, 63 (5), 1529–44.
- Sengupta, Rajdeep and Craig P. Aubuchon (2008), "The Microfinance Revolution: An Overview," *Federal Reserve Bank of St. Louis Review*, 90 (January/February), <https://files.stlouisfed.org/files/htdocs/publications/review/08/01/Sengupta.pdf>.
- Shi, Huanhuan, Shrihari Sridhar, Rajdeep Grewal, and Gary Lilien (2017), "Sales Representative Departures and Customer Reassignment Strategies in Business-to-Business Markets," *Journal of Marketing*, 81 (2), 25–44.
- Shin, Jiwoong and K. Sudhir (2010), "A Customer Management Dilemma: When Is It Profitable to Reward One's Own Customers?" *Marketing Science*, 29 (4), 671–89.
- Sorenson, Olav and Michelle Rogan (2014), "(When) Do Organizations have Social Capital?" *Annual Review of Sociology*, 40, 261–80.
- Steenburgh, Thomas J. (2008), "Effort or Timing: The Effect of Lump-Sum Bonuses," *Quantitative Marketing and Economics*, 6 (3), 235–56.
- Venkatesan, Rajkumar and V. Kumar (2004), "A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy," *Journal of Marketing*, 68 (4), 106–25.
- WorldatWork (2016), "Sales Compensation Programs and Practices," (October 2016), (accessed March 21, 2019), <https://www.worldatwork.org/docs/research-and-surveys/survey-brief-sales-compensation-programs-and-practices-2016.pdf>.
- Zhang, Jonathan Z., Oded Netzer, and Asim Ansari (2013), "Dynamic Targeted Pricing in B2B Relationships," *Marketing Science*, 33 (3), 317–37.