A Structural Model of a Multitasking Salesforce: 
Job Task Allocation and Incentive Plan Design

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We develop the first structural model of a multitasking salesforce to address questions of job design and incentive compensation design. The model incorporates three novel features: (i) multitasking effort choice given a multidimensional incentive plan; (ii) salesperson’s private information about customers and (iii) dynamic intertemporal tradeoffs in effort choice across the tasks. The empirical application uses data from a microfinance bank where loan officers are jointly responsible and incentivized for both loan acquisition repayment but has broad relevance for salesforce management in CRM settings involving customer acquisition and retention. We extend two-step estimation methods used for unidimensional compensation plans for the multitasking model with private information and intertemporal incentives by combining flexible machine learning (random forest) for the inference of private information and the first-stage multitasking policy function estimation. Estimates reveal two latent segments of salespeople—a “hunter” segment that is more efficient in loan acquisition and a “farmer” segment that is more efficient in loan collection. We use counterfactuals to assess how (1) multi-tasking versus specialization in job design; (ii) performance combination across tasks (multiplicative versus additive); and (iii) job transfers that impact private information impact firm profits and specific segment behaviors.

Key words: Salesforce compensation, multitasking, multi-dimensional incentives, private information, adverse selection, moral hazard

1. Introduction

Personal selling employs approximately 10% of the US labor workforce; selling-related expenditures are about 5% of the US GDP at approximately $1 trillion (Zoltners et al. 2008). These shares are even greater in the retail, financial services, automobiles, banking, consulting and technology sectors (Misra 2019). As a benchmark, the total advertising

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spending in the United State as of 2019 is around $200 billion. It is clear that the efficiency gains from more effective sales force management can have a significant impact in many industries and even across the economy.

Despite the much higher spending, the empirical research on personal selling is much more limited as the data on advertising tends to be more widely available and measured in richer detail, especially in digital settings. Although the empirical research on personal selling has seen a recent spurt as richer data on compensation plans and salesforce performance has become available, the focus of the research thus far has mostly been limited to various types of compensation plans in response to the unidimensional metrics of performance (e.g., sales). For example, Misra and Nair (2011) and Chung et al. (2013) study the role of linear commission versus nonlinear incentive plans involving sales quotas and bonuses for exceeding quota, while Chan et al. (2014) study salesperson behavior under team versus individual performance-based incentives.

This paper expands the focus of the empirical research in salesforce management to broader issues that go beyond compensation such as (1) job design when firms need the salesforce to perform multiple tasks and (2) how performance on different tasks should be combined to determine overall performance and compensation.

We begin with the problem of job design—how should a firm allocate tasks among sales employees? The issue was first addressed in Holmström and Milgrom (1991) who laid the theoretical foundations for the study of job design and task allocation in a principal agent framework. In this paper, we ask the following questions: Should tasks be divided across employees, with each employee assigned a specialized task? Or should each employee have joint responsibility across multiple tasks? The answers depend on the following fundamental specialization-multitasking trade-off, i.e., while specialization can produce efficiency gains, as each employee can be allocated tasks to which she is better suited, multitasking can produce efficiency gains by internalizing any production complementarities across multiple tasks. Which of these two effects dominate is an empirical question.¹

Next, in multitasking, how should the firm combine performance outcomes across tasks in incentive-based compensation plans? For example, should performance on different tasks

¹It is potentially possible to have teams of employees be responsible for the joint outcomes across multiple tasks, with individual salespeople specializing in a task. In this paper, we abstract away from such job designs in this paper.
be combined additively or multiplicatively when determining overall compensation? Mac-
Donald and Marx (2001) show that when there are intrinsic production complementarities
across tasks but no payoff complementarities for agents, an additive scheme can lead to
adverse specialization because employees perceive the two tasks as substitutes for their
effort and therefore choose to specialize more on the task that is less costly to the employee
than is optimal for the firm. To address this problem, they recommend a multiplicative
incentive scheme that makes employee payoff to be also complementary in the two tasks,
thus producing greater alignment with the firm payoffs for any given level of compensation.
However, it is an open question as to whether an additive or multiplicative scheme is better
when there are both production complementarities for the firm and payoff complementar-
ities for the agents across tasks.

In this paper, we investigate the job task allocation and incentive-based compensation
plan design problem in the context of a bank’s salesforce (loan officers) that is responsible
for both loan acquisition and loan collection. In our context, we specifically seek to answer
the question of whether a salesperson should be responsible for both acquiring new loans
and collecting the loans, for which there are complementarities in the acquisition and
collection tasks because loans that are easier to acquire tend to be harder to collect on.
Specifically, bad customers who have worse outside options tend to be easier to acquire;
however, it is more difficult to collect repayments from them. The question has parallels
to the customer relationship management (CRM) literature, in which sales employees may
either specialize or be jointly responsible for customer acquisition and retention. Further, if
indeed loan officers are indeed responsible for loan acquisition and repayment, how should
performance on these dimensions be combined overall in terms of their incentives?

Answering the questions of job task allocation (loan acquisition and repayment) and
compensation design (how to combine performance on the two tasks) in our context requires
that we address two fundamental challenges. The first is “private information”, as sales-
people have private information about their customers’ profitability that is not available
to the firm; however, this information can impact their choice of effort allocation across
tasks. While private information may help improve efficiency by allowing salespeople to
target the right customers for acquisition and repayment, it can also lead to incentive mis-
alignment and lower firm profits because it can encourage the salesperson to selectively
acquire the easier-to-acquire “bad” customers, who are less likely to repay. The second is
a “dynamic intertemporal tradeoff” in effort allocation across new loan acquisition and repayment tasks when there is heterogeneity in loan repayment probabilities. For example, a salesperson acquiring easier-to-acquire loans today to do well on the acquisition metric must be concerned about the trade-off on future payoffs because such a customer is less likely to repay the loans. Thus there is payoff complementarity for salespeople among the two tasks, whether the two tasks are combined additively or multiplicatively. Hence, the question of whether the additive or multiplicative scheme is superior is an open empirical one.

To address these questions, we develop and estimate the first structural model of multitasking employees in the literature. The structural model has potentially broad applicability across fields of marketing, operations management, organizational behavior and organizational economics. Relative to the existing structural models in salesforce compensation, the model incorporates novel features such as private information among salespeople and the intertemporal trade-offs faced by the loan officers in effort allocation across the loan acquisition and repayment tasks. Further, it allows for salesforce heterogeneity in the costs of performing loan acquisition and repayment collection tasks.

Our empirical application is based on a microfinance bank in Mexico. We estimate the structural model of multitasking by loan officers at the bank using data on salesforce performance and compensation matched with the loans generated by the loan officers and information about the loan characteristics and repayment outcomes. It is useful to consider the features of the data that allow us to incorporate additional features such as multitasking and private information relative to the existing structural literature on salesforce compensation. First, in contrast to the existing literature, which observes only sales performance outcomes, we observe not only new loan acquisition volumes, but also the repayment performance on past loans, which allows us to model the multitasking effort in both acquisition and maintenance to collect loans. Second, there are several features of the data that allow us to study the role of private information. We observe ex-post loan repayment behavior for individual loans in combination with ex-ante loan characteristics, and salesperson states that impact incentives to exploit private information at the time of loan acquisition and maintenance. By controlling the effect of observed ex-ante loan characteristics and salesperson states, we are able to back out unobservable private type
about loans. Further, the exogenous variation on whether salespeople have private information due to salesperson transfers allows us to identify differences in effort allocated when salespeople have private information or not.

Our estimation strategy extends and adapts the two-step estimation strategy in Chung et al. (2013) to estimate a structural model of a multitasking salesforce with unobserved salesperson heterogeneity and salesperson private information. We use the EM algorithm estimation framework in Arcidiacono and Miller (2011) that estimate their dynamic structural model using the iterative decomposition approach in Arcidiacono and Jones (2003) to accommodate latent class heterogeneity. Our extension of the approach allows us to accommodate multitasking and private information, which we will explain below.

There are several key challenges for estimation in the incorporation of multitasking and private information. First, with multitasking (acquisition/maintenance) and private information (good/bad loans), salespeople must decide on four levels of effort related to the acquisition and maintenance of good and bad loans. This leads to a system of equations with a combined set of salesperson state variables and other exogenous factors that affect demand. Hence the nonparametric first stage estimation is significantly more complicated than in Chung et al. (2013) who use a Chebyshev polynomial for nonparametric estimation. Here we use a machine learning model—random forest with cross-validation—to avoid overfitting to estimate the first-stage loan production functions in which flexible nonparametric effort policy functions are embedded. Second, we note that private information about loans is not directly observed by the researcher, but must be inferred from the ex-ante outcomes and salesperson states and observable loan characteristics. A particular challenge here is that salesperson states and types affect effort choices and thus loan outcomes. Hence, inferring latent loan types from loan outcomes require us to control for the latent salesperson types. Similarly, inferring latent salesperson types requires us to know the latent loan types. To address this issue, we develop an iterative algorithm whereby we begin with some prior distribution about loan types and salesperson types, and then iterate the inference procedure of loan types and salesperson types until there is convergence in the two. We provide more details on the estimation algorithm in Section 5.

Our estimation results reveal two distinct segments of loan officers: a larger “hunter” segment and a smaller “farmer” segment. We find that the “hunter” type segment has a relatively low acquisition cost and is more efficient at “hunting” for new customers, whereas
the “farmer” type segment has a relatively low maintenance cost and is more efficient at “farming” existing customers to obtain repayments. The hunters are also more effective in using private information than the farmers in that they can more effectively identify and acquire the easier-to-acquire segment of lower quality customers—thus, they are more likely to indulge in moral hazard through adverse customer selection.

In the counterfactual simulations, we first compare specialization versus multitasking in job design. Since our estimates indicate that there is a hunter segment and a farmer segment, a natural “specialization”-based job design for the bank is the allocation of all acquisition tasks to the hunter segment and all maintenance tasks to the farmer segment. We find that the firm is better off with multitasking—by making salespeople responsible for both loan acquisition and maintenance. In other words, the cost of adverse customer selection by salespeople due to incentive misalignment between the complementary acquisition and repayment task dominates the efficiency gains obtained from specialization.

Our second counterfactual results show a nuanced trade-off in the use of additive versus multiplicative combination of performance across tasks. We find that, consistent with the findings of MacDonald and Marx (2001), the multiplicative scheme helps the firm avoid adverse specialization by preventing the hunter segment from focusing excessively on acquiring new loans, especially bad ones. However, with the farmer segment for whom given their high (low) cost to acquire (maintain) loans, the multiplicative scheme backfires by forcing them to spend more effort on acquisition and end up with more bad loans that become delinquent than they would have with the additive scheme. Thus, our results add theoretical nuance to the role of additive versus multiplicative schemes to avoid adverse specialization relative to MacDonald and Marx (2001), when there is already inbuilt complementarity in agent payoffs among tasks.

Finally, our counterfactual on transfers shows that private information is a double-edged sword: hunters abuse it to acquire easier-to-acquire but less profitable loans, but farmers take advantage of it to selectively monitor and collect loans. Thus, hunters’ usage of private information hurts the firm whereas farmers’ usage of private information helps the firm.

The rest of the paper is organized as follows. Section 2 describes the related literature and thereby situates the current paper. Section 3 describes the institutional setting and the data. Sections 4 and 5 describe the model and estimation. Section 6 discusses the estimation results while Section 7 reports the counterfactual analysis. Finally, Section 8 concludes.
2. Related Literature

Our paper contributes to several streams of literature. First, our paper is related to the theoretical literature on the multitasking principal-agent model (see, e.g., Holmström and Milgrom 1991, Baker et al. 1994, Dixit 2002). A key finding of this literature is that incentivizing one dimension of multiple tasks may lead to the agent shirking on other performance dimensions. Holmström and Tirole (1993), for example, find that incentive schemes that reward only immediately realized profits can lead agents to sacrifice long-run profits. To solve this moral hazard problem, Godes (2004) proposes the division of labor for salespeople who work on technologically substitutable tasks. Alternatively, MacDonald and Marx (2001) consider the situation where the principal prefers the agent to spend effort on various tasks whereas the agent prefers to spend effort only on less costly tasks, as in our setup. In such a case, the agent tends to engage in “adverse specialization,” and hence the optimal contract has a multiplicative incentive structure across tasks that makes tasks complementary from the agent’s perspective. Although this idea is close to the compensation plan employed by the bank we study, the setup in MacDonald and Marx (2001) is inherently static in that various tasks’ performance outcomes affect only agents’ incentives in the same period. The current paper empirically studies the setting where effort choices have intertemporal effects, necessitating the modeling of forward-looking dynamics.

The second stream of literature related to our study is the empirical literature on studying multitasking agents. Agarwal and Wang (2009) and Agarwal and Ben-David (2018) exploit an exogenous change in the compensation structure of a bank in the US to show that sales incentives encourage loan officers to take excessive risk and increase defaults. To address this issue, they argue that incentives must be complementary in terms of performance across the multiple tasks. Using a commercial bank data set, Behr et al. (2019) find that the contract covering both loan acquisition and loan performance is effective for stimulating overall greater effort to extend loans while maintaining loan quality. Kim

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3 There has been recent interest in finance about loan officer moral hazard in loan acquisition in response to acquisition incentives (e.g., Heider and Inderst 2012, Cole et al. 2015, Varas 2017); however, the studies do not address issues of multitasking and how retention incentives can mitigate the moral hazard. Further, the papers do not develop structural models of loan officer behavior.

4 Their performance metric is based on the portfolio size and the performance; however, the relationship is nonlinear. The authors use this variation to identify the effects of the contract.
et al. (2019) study the same bank setting and find evidence of salesperson moral hazard in that salespeople have private information about customers, which leads to adverse loan selection, i.e., salespeople’s acquisition incentives incentivize them to acquire low quality loans. They also find that because loan officers are responsible for loan maintenance as well as acquisition, the maintenance incentives mitigate the adverse selection in loans. By contrast, Bracha and Fershtman (2012) do not find evidence for a distorting effect of the pay-for-performance scheme in which the overall performance is determined by the combination of the two observable and contractible tasks.

To the best of our knowledge, empirical work on job design remains scarce despite a highly influential theoretical paper by Holmström and Milgrom (1991). A notable exception is Baker and Hubbard (2003) who study the effect of new technology on asset ownership and job design in the trucking industry.(e.g., Antrás 2003, Feenstra and Hanson 2005).\(^5\)

In this paper, we consider job task allocation and incentive design for salespeople by developing and estimating a dynamic structural model of a multitasking salesforce with private information about customers.

Our paper is also clearly related to the empirical literature on salesforce compensation. Although the early work tended to take the form of descriptive analyses of salesforce compensation practices and involve testing predictions of the principal agent theory in compensation plan design (e.g., Joseph and Kalwani 1998, Coughlan and Narasimhan 1992), there has recently been a surge of work that estimates structural models using data from salesforce performance outcomes in response to incentive schemes at the firm (e.g., Misra and Nair 2011, Chung et al. 2013, Schöttner 2016). However, these papers thus far have focused on single-tasking salesforces. Our paper adds to this literature by developing a structural model of multitasking in response to multi-dimensional incentives and investigate job allocation and incentive design under such a situation. In particular, the nature of multitasking in our model induces intertemporal dynamics in terms of effort allocation across multiple tasks—acquisition and maintenance. The structure of this problem is particularly useful for modeling salesforce management in CRM-type settings when salespeople are jointly responsible not only for customer acquisition but also for other activities.

\(^5\) Recently, the role of IT on job task allocation has received attention. For example, computer science studies (e.g. Ho and Vaughan 2012, Ho et al. 2013, Tong et al. 2016) develop algorithms to solve the problem of job allocation between humans and machines or among crowdsourced workers.
such as customer maintenance, retention and growth that increase customer lifetime value. We therefore hope that our model will serve as a workhorse model in multitasking settings, and especially for those involving intertemporal dynamics as in CRM settings.

3. Institutional Setting and Data

This section describes our empirical setting and data. We highlight the multiple responsibilities of a salesperson, incentivized by a multi-dimensional compensation plan and the role of salesperson private information.

3.1. Institutional Setting

Our empirical setting is a Mexican microfinance bank. As is typical in microfinance, given the needs of the target segment, the loans are made without collateral on relatively small amounts (the average amount is $670), with high interest rate (the average monthly rate is 7.3%), and short maturity periods (the average length is 4.1 months). Despite the 7.3% monthly interest rate, the average monthly return of the loans is 5.0%, indicating that the delinquency rate is very high as is fairly common in the microfinance sector in emerging markets (Sengupta and Aubuchon 2008). Most customers are small businesses (e.g. grocery shop owners, tailors).

The empirical setting is ideal for studying multitasking because the loan officers at the bank are jointly responsible for both loan acquisition and loan maintenance to ensure repayment, and their incentive compensation is jointly tied to performance in both dimensions. At the acquisition stage, the loan officers recruit borrowers through referrals or personal visits, accept loan applications, and then recommend loan terms to the bank. The bank gives the loan officers significant discretion on whether to approve a loan but then holds the officers responsible to ensure that outstanding loans are repaid on time (e.g., through phone calls and in-person visits). Note that interest rates are determined by the bank based on the public information about the borrowers (i.e., a 1–5 credit rating with 5 as best, constructed with data from an external agency).

The salesperson’s monthly compensation at the bank includes two parts: salary and bonus. The salary ($S_{jt}$ for officer $j$ at period $t$) is determined solely by seniority, not performance, whereas the bonus ($B_{jt}$) depends on customer acquisition and maintenance performance. Acquisition performance is benchmarked against one’s own past performance to generate an acquisition index (Acquisition index $A_{jt}$ is defined as $A_{jt} = N_{jt}/Q_{jt}$ where
$N_{jt}$ is the amount of new loans acquired by officer $j$ at period $t$, and $Q_{jt}$ is the acquisition quota, which depends on the amount of active loans of officer $j$ at the beginning of period $t$). Maintenance index is based on the value of collected loans relative to that of outstanding loans ($M_{jt} = g(R_{jt}/O_{jt})$) where $R_{jt}$ is the amount of repaid loans collected by officer $j$, $O_{jt}$ is the outstanding value of loans in salesperson $j$’s portfolio due at period $t$, and $g(.)$ is an increasing step function detailed in Table A1 in the appendix. The final bonus is the product of the base salary, acquisition index, and maintenance index (i.e., $B_{jt} = S_{jt}A_{jt}M_{jt}$); thus, receiving zero points in any category would earn no bonus at all. Note that because the incentives are based on combination of acquisition and maintenance performance, the officers must not only balance their efforts between acquisition and maintenance tasks at each point of time, but they must also consider a dynamic trade-off between the short-term benefits of acquiring (possibly lower quality) customers to improve acquisition performance and its long-term negative effects on maintenance performance.

Throughout a loan cycle, the loan officers obtain private information about customers that the bank cannot observe such as customers’ motives, needs, financial capabilities/liabilities, and outside options, which can create a sort of “relational capital” between the loan officers and their clients. Salespeople may use such private information in loan decisions beyond the public information in the firm’s database (e.g., credit rating), because the private information not only informs the probability of default but also the cost of acquiring and maintaining loans (Kim et al. 2019). Therefore, salespeople may abuse it to maximize their payoffs at the expense of the firm, by acquiring easier-to-acquire lower-quality customers to perform well in the short-run on the acquisition metric. However, the maintenance incentive can serve to discipline the loan officers from engaging in the adverse selection of customers. Kim et al. (2019) show that the customer maintenance performance metric not only reduces loan defaults (better repayment), but also indirectly moderates the adverse selection as forward-looking salespeople anticipate the future consequences of current (bad) customer acquisition.

A unique feature of the setting is that the bank randomly relocates loan officers from their current branch to another branch. Transfers are common in the retail banking sector.

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6 In our setting, a salesperson can obtain private information, which is not observable to the bank, as most of the loan transactions happen outside the branch of the bank. When a salesperson visits a customer’s business to ask the need for loans, remind customers of repayment dates or collect loans, she learns about the customers including getting to know how well a customer is running his business, or if a customer is experiencing unexpected financial hardship, etc.
to avoid the potential abuse of private information by loan officers, which could lead to the adverse selection of new customers (Fisman et al. 2017). In our setting, the transfers, both in terms of timing and location, are entirely randomly determined. The randomness in timing is designed to prevent loan officers from engaging in strategic acquisition behaviors when they expect to be transferred.\(^7\)

A (randomly) transferred salesperson takes over and monitors the loans acquired by the predecessor who left the branch. The transferred salesperson’s maintenance bonus does not depend on the loans she has collected in the previous branch, but depends solely on the repayment outcomes of the loans she took over after transfer, thus making these states exogenous for the loan officer upon transfer. In the model, we assume that continuing (i.e. nontransferred) salespeople have private information about loan profitability whereas transferred salespeople are treated the same as those who are without private information. This exogenous variation in private information helps us evaluate the role of private information on salesperson behavior.

### 3.2. Data

Our data consist of the following: (1) salesperson-level data that contain each salesperson’s characteristics, and monthly performance and compensation as analyzed in the previous empirical salesforce compensation literature and (2) loan-level transaction data that contain each loan’s characteristics and monthly repayment outcomes. The two datasets are matched based on the identity of a salesperson who originates or monitors each loan in each period.\(^8\) The data we use for estimation comes from the performance and compensation outcomes of 229 salespeople over a 14-month period from January 2009 to February 2010. In all, we obtain 2,648 observations (months of performance outcomes and compensation) across the 229 salespeople. The performance and compensation outcomes are aggregated/summarized from the 100,250 loans for which we observe detailed repayment outcome data over the life of the loan.\(^9\)

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\(^7\) In the Online Appendix, we empirically check that the implementation of the transfer policy is truly random by testing where transfers are correlated with salesperson observable characteristics such as tenure, the length of time since last transfer, or past performance. Indeed, we find no correlation.

\(^8\) Salespeople were removed from the final sample if their aggregate performance did not match with the compensation index (i.e., some of their loans that seemingly contributed to their bonus are missing in the data). We dropped 29,589 loans from the data.

\(^9\) We do not observe much salesperson performance in April 2009, when an outbreak of swine flu has spread in Mexico and severely impacted Mexico City, where over 80% of the branches are located. The institution was not
Table 1 reports summary statistics of our panel data. Out of the 2,648 salesperson-month observations in the data, 4.8% of observations have transfers. A total of 22.3% of the salespeople experience at least one transfer during our 14-month observation window. The salespeople have worked for the bank for 25.5 months on average, and they acquire 347,470 pesos (approximately US$25,365 as of 2009) of new loans, have 888,300 pesos (approximately US$64,845 as of 2009) of loans in the portfolio and collect 772,847 pesos (approximately US$56,415 as of 2009) of past loans each month. The acquisition index benchmarked against the quota is 0.82 on average (i.e., salespeople achieve 82% of quota on average), and the maintenance index benchmarked against the amount of loans in the portfolio is 0.86 on average. On average, the loan officers’ bonus was 55% of their salary.

| Transfer | 2648 | Yes (4.8%) |
| Number of Transfer | 229 | 0 (77.7%), 1 (21.0%), 2+ (1.3%) |

<table>
<thead>
<tr>
<th>Tenure (months)</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
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<tr>
<td>New Loan Amount (1000 pesos)</td>
<td>2648</td>
<td>347.5</td>
<td>326</td>
<td>10</td>
<td>3066</td>
</tr>
<tr>
<td>Monthly Outstanding Loan Amount (1000 pesos)</td>
<td>2648</td>
<td>888.3</td>
<td>748.2</td>
<td>0</td>
<td>5209</td>
</tr>
<tr>
<td>Monthly Repayment Amount (1000 pesos)</td>
<td>2648</td>
<td>772.8</td>
<td>695.8</td>
<td>0</td>
<td>5052.7</td>
</tr>
<tr>
<td>Acquisition Quota (1000 pesos)</td>
<td>2648</td>
<td>429.2</td>
<td>492.8</td>
<td>13.2</td>
<td>2938.8</td>
</tr>
<tr>
<td>Acquisition Index</td>
<td>2648</td>
<td>0.82</td>
<td>0.42</td>
<td>0.02</td>
<td>3.19</td>
</tr>
<tr>
<td>Maintenance Index</td>
<td>2648</td>
<td>0.86</td>
<td>0.23</td>
<td>0</td>
<td>1.25</td>
</tr>
<tr>
<td>Bonus point</td>
<td>2648</td>
<td>0.55</td>
<td>0.3</td>
<td>0</td>
<td>2.35</td>
</tr>
</tbody>
</table>

Note that we do not know the exact formula for the acquisition quota $Q_{jt}$. However, according to the firm’s policy, we know that a continuing salesperson’s acquisition quota, which is used as a basis for the acquisition index, is a function of (1) the amount of outstanding loans in salesperson $j$’s portfolio at the beginning of period $t$, $O_{jt}$; and (2) the lagged acquisition quota $Q_{j,t-1}$. We will infer the transition of quota from the data and explain our algorithm for inferring quotas in the estimation section.
3.3. Model-free Evidence

Before going to the structural model, we present the model-free evidence for two key features underlying the structural model— (i) how maintenance incentives impact the quality of the acquired loans, conditional on observable quality as represented by the credit rating; and (ii) the presence and effect of salesperson private information on the quality of the acquired loans.

We begin with the effect of maintenance incentives on the quality of the loans acquired. Figure 1 plots the loans’ public credit rating on the horizontal axis and the average ex post annual Internal Rate of Return of loans acquired in period \( t \) as a measure of realized loan quality on the vertical axis. Within each rating, we split the observations at the median of the share of delinquent loans in period \( t - 1 \). The figure shows that the average IRR of the acquired loans is greater when the share of delinquent loans is below the median for every rating level. This finding indicates that loan officers acquire ex post higher quality loans when they are under the pressure of ensuring sufficient repayment from the loans in their portfolio. Thus, the maintenance incentives can reduce the incentive misalignment between the bank and the loan officers due to acquisition incentives.

Next, we show that a salesperson’s private information impacts the quality of the acquired loans. For this aspect, we exploit the firm’s transfer policy because transfers generate exogenous variation in the degree of the private information within salespeople. By comparing the ex post loan quality (IRR) of a transferred loan officer (i.e., without private information) to that of a continuing salesperson (i.e., with private information), we can
measure the effect of the private information on salesperson behavior. Figure 2 plots the average ex post return of the loans acquired by salespeople who were transferred to new branches at the beginning of the period and that of the loans acquired by continuing salespeople in the same branch (i.e. salespeople who were not transferred at the beginning of the period) for each credit rating. The figure shows that the loans acquired by the transferred salespeople have a higher IRR on average than those acquired by the continuing salespeople. This finding suggests that salespeople use their private information to selectively bring in easier-to-acquire but ex post lower quality loans.\footnote{For evidence that the effect of maintenance incentives and transfers on the quality of acquired loans remain robust and statistically significant even after controlling for other relevant factors simultaneously, refer to the regressions reported in the section on “Acquisition: Selection Effects When Originating Loans” in Kim et al. (2019).}

4. Model
Motivated by the model-free evidence, we now develop a dynamic structural model of the salesperson’s multitasking behavior in the presence of private information. A salesperson exerts effort on acquisition and maintenance tasks in response to the multi-dimensional incentive scheme discussed above. Further, the salesperson with private information about customer profitability takes into account the dynamic trade-off of acquiring or maintaining different (private) types of loans. While riskier (conditional on public information) loans are easier to acquire, they are more likely to default in the future, thus hurting maintenance performance and requiring greater maintenance effort in the future. We model unobservable ex ante loan types in the population as a binary discrete distribution—“good” (ex
Figure 3  Within-Period Timing of Salesperson Model

Ante profitable, harder-to-acquire loans) and “bad” (ex ante unprofitable, and easier-to-acquire loans), where the proportion of good types in the population can vary by observable credit rating. We expect the proportion of good type loans to increase monotonically by observable credit rating.

Figure 3 describes the timing of the model within a time period (month). At the beginning of the period, the firm randomly chooses which salespeople will be transferred from their current branch. Then the salesperson observes the compensation plan and her states. Over the period, the salesperson chooses effort level on the multiple dimensions. At the end of the period, the outcomes are realized based on both effort and shocks and then the salesperson receives compensation based on the realized performance outcomes. After the outcomes are realized, the states are updated and the game moves to the next period.

We next elaborate on the seven elements of the model: transfers, compensation plan, actions, state variables, performance outcome functions, state transitions, flow utility function and Bellman equation.

4.1. Transfers
At the beginning of each period, the firm chooses which salespeople will be transferred and to where. This transfer decision is deliberately random as the firm does not want the salesperson to anticipate whether and where she will be transferred to discourage moral hazard in providing loans. Such “instant” transfers are feasible because the bank operates within one large metropolitan area and a salesperson can easily commute to any assigned territory within the operational area. Upon transfer, the salesperson does not have any information about the customers in the new territory and hence cannot ex ante infer the borrower type (good or bad). Continuing salespeople (who have not been transferred in a given period) are assumed to have perfect information about the borrower type. We assume that salespeople need one period to obtain private information.\(^{11}\)

\(^{11}\) Our results are robust to the number of months (we tested 2 and 3) it takes for a salesperson to acquire private information after a transfer.
4.2. Compensation Plan

The compensation plan is based on composite performance along the acquisition and maintenance tasks. Acquisition performance is measured using an acquisition index $A_{jt}$ of salesperson $j$ in period $t$. Specifically, and as explained in Section 3, $A_{jt} = N_{jt}/Q_{jt}$, where $N_{jt}$ is the amount of new loans acquired and $Q_{jt}$ is the acquisition quota. The quota-setting policy is described in section 4.4.

Maintenance performance is measured using a maintenance index $M_{jt} = g(R_{jt}/O_{jt})$, where $R_{jt}$ is the amount of repaid loans, $O_{jt}$ is the outstanding value and $g(\cdot)$ is an increasing function of $R_{jt}/O_{jt}$.\(^{12}\)

The overall bonus compensation is a product of the two indices: $B_{jt} = A_{jt} \times M_{jt}$.\(^{13}\) We denote the compensation plan as $\Gamma = \{Q_{jt}, g(\cdot)\}$.

4.3. Actions

The salesperson’s action set depends on whether the salesperson is transferred or not due to the availability or unavailability of private information. The continuing salesperson knows the unobservable loan types and can hence choose four levels of effort: acquisition effort for good and bad loan types, denoted as $e_{jt}^{AG}$ and $e_{jt}^{AB}$ and maintenance effort for good and bad loan types, which are denoted as $e_{jt}^{MG}$ and $e_{jt}^{MB}$.\(^{14}\)

In contrast, the transferred salesperson cannot distinguish loan types and chooses only total acquisition effort $e_{jt}^{A}$ and total maintenance effort $e_{jt}^{M}$.\(^{14}\)

4.4. State Variables

For a salesperson without private information, the state variables $s_{jt}^{A}$ that determine acquisition effort $e_{jt}^{A}$ include the amount of outstanding loans $O_{jt}$, the amount of loans that would expire at the end of period $E_{jt}$, acquisition quota $Q_{jt}$, and salesperson tenure $\tau_{jt}$. $O_{jt}$ and $E_{jt}$ as well as the amount of loans acquired in period $t$ determine the portfolio size that the salesperson $j$ needs to collect from the next period as we will discuss in Section

\(^{12}\) Details of the $g(\cdot)$ function are provided in the appendix.

\(^{13}\) We normalize the payoff by a salesperson’s salary because there is little variation in salary across salespeople, and we do not observe all salespeople’s salary in all periods.

\(^{14}\) The allocation of total efforts into acquisition and maintenance efforts across good and bad loans is determined by the population distribution of these loans in each branch/period. In other words, letting $p_{jt}^{G}$ be the probability of a loan being a good loan in the branch at which salesperson $j$ works at time $t$, $e_{jt}^{A}$ is allocated to good loans with probability $p_{jt}^{G}$ and to bad loans with probability $1 - p_{jt}^{G}$. We assume that the salespeople know the distribution of the type of loans in the market. In our empirical specification, we compute the fraction of good loans among loans in each branch/period to estimate $p_{jt}^{G}$. Monitoring efforts are similarly allocated.
4.6. Acquisition quota $Q_{jt}$ directly affects $e^A_{jt}$ through the acquisition index. We include $\tau_{jt}$ as a state variable to proxy salesperson $j$’s ability and knowledge.

Similarly, maintenance effort $e^M_{jt}$ is affected by the amount of outstanding loans, the lagged amount of repaid loans $R_{jt-1}$, and tenure. Note that the amount of repaid loans in period $t-1$ ($R_{jt-1}$) enables the salesperson to be aware of the repayment likelihood of existing loans. \(^{15}\)

A salesperson with private information has additional state variables because she can track the amount of outstanding loans and the amount of expiring loans by loan type. State variables $s_{jt}^{AG}$ that determine acquisition effort for good loans $e_{jt}^{AG}$ include the amount of outstanding good loans $O_{jt}^G$, the amount of good loans to be expired at the end of period $E_{jt}^G$, acquisition quota, and tenure. State variables $s_{jt}^{AB}$ that affect acquisition effort for bad type loans $e_{jt}^{AB}$ are similarly defined.

Finally, state variables for maintenance efforts for type $\omega$ loans, $s_{jt}^M$ (\(\omega \in \{B, G\}\)), include the outstanding loan amount of type $\omega$, $O_{jt}^\omega$, the lagged amount of repaid type $\omega$ loans $R_{jt-1}^\omega$, and tenure. Table 2 summarizes the state variables for each action.

\(^{15}\) Kim et al. (2019) find that a salesperson changes maintenance effort depending on her lagged maintenance bonus $M_{jt-1}$. We use the lagged amount of repaid loans $R_{jt-1}$ here that directly affects the lagged maintenance bonus $M_{jt-1}$.
4.5. Loan Officer Production Functions

Following Misra and Nair (2011) and Chung et al. (2013), we model loan officer outcomes as the production functions arising from three components: (1) loan officer effort policy functions; (2) exogenous production shifters and (3) idiosyncratic production shocks not known to loan officers when choosing effort. The key differences with respect to the prior research in addressing multi-dimensional performance with private information are as follows: (1) we accommodate multiple dimensions of outcomes (acquisition and maintenance); (2) we allow for private information in terms of good and bad loan outcomes; this also implies that effort choice will also include acquisition and maintenance effort on good and bad loans and (3) we allow for correlation in the shocks across the outcome equations.

Acquisition outcomes for the salesperson with private information are the amount of new good loans acquired \( N_{jt}^G \); and the amount of new bad loans \( N_{jt}^B \). We model the acquisition outcomes as follows:

\[
N_{jt}^G = e_{jt}^{AG}(s_{jt}^{AG}, s_{jt}^{\backslash AG}; \lambda^{AG}) + f(X_{jt}; \beta^{AG}) + \epsilon_{jt}^{AG},
\]

\[
N_{jt}^B = e_{jt}^{AB}(s_{jt}^{AB}, s_{jt}^{\backslash AB}; \lambda^{AB}) + f(X_{jt}; \beta^{AB}) + \epsilon_{jt}^{AB},
\]

where \( e_{jt}^{AG}(\cdot; \lambda^{AG}) \) and \( e_{jt}^{AB}(\cdot; \lambda^{AB}) \) are the acquisition effort policy function for good and bad loans respectively, \( f(\cdot; \beta^{AG}) \) and \( f(\cdot; \beta^{AB}) \) are the effects of exogenous shifters \( (X_{jt}) \), and \( \epsilon_{jt}^{AG} \) and \( \epsilon_{jt}^{AB} \) are idiosyncratic shocks such as unexpected market condition in each market/period that are neither anticipated nor observed by salesperson \( j \) before the effort choices. We will explain the variables included in \( X_{jt} \) in Section 5.

Note that the acquisition effort policy function for good loans are functions of both the state variables associated with other tasks \( s_{jt}^{\backslash AG} \) as well as the state variables associated with acquiring good loans \( s_{jt}^{AG} \), and \( \lambda^{AG} \) is the set of parameters that map the state variables to effort. \( e_{jt}^{AG} \) is affected by \( s_{jt}^{\backslash AG} \) because acquisition and maintenance efforts are jointly chosen. Hence, outcomes are determined by all state variables through effort choices for other actions.16

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16 For example, choosing the acquisition effort for good loans, \( j \) takes into account states that affect acquisition effort of bad loans \( (e_{jt}^{AB}) \), which will affect the distribution of loan types in the subsequent periods. At the same time, \( j \) allocates limited effort to acquisition and maintenance tasks in period \( t \) and thus considers states that affect maintenance effort of each type of loans \( (e_{jt}^{MG} \text{ and } e_{jt}^{MB}) \) in the choice of acquisition effort for good loans. Among the states that affect maintenance effort, lagged repaid amount of good and bad loans \( (R_{jt-1}^G \text{ and } R_{jt-1}^B) \) inform \( j \) of the required maintenance effort under the current portfolio, and help her make acquisition decisions accordingly to balance immediate acquisition cost and future repayment likelihood of all the loans in her portfolio.)
Note that when the salesperson does not have private information, the allocation of efforts across loan types is out of the salesperson’s control and determined by the fraction of good and bad type loans in population.\

In the same manner, we model the maintenance outcomes, the amount of repaid good loans $R_{jt}^G$ and the amount of repaid bad loans $R_{jt}^B$, as follows:

$$R_{jt}^G = e_{jt}^{MG}(s_{jt}^M; s_{jt}^M; \lambda_{jt}^M) + h(X_{jt}; \beta_{jt}^M) + \epsilon_{jt}^M,$$

$$R_{jt}^B = e_{jt}^{MB}(s_{jt}^M; s_{jt}^M; \lambda_{jt}^M) + h(X_{jt}; \beta_{jt}^B) + \epsilon_{jt}^B,$$

where $e_{jt}^{MG}(\cdot; \lambda_{jt}^M)$ and $e_{jt}^{MB}(\cdot; \lambda_{jt}^M)$ are the maintenance effort policy function for good and bad loans respectively $h(\cdot; \beta_{jt}^M)$ and $h(\cdot; \beta_{jt}^B)$ are the effects through exogenous shifters $X_{jt}$, and $\epsilon_{jt}^M$ and $\epsilon_{jt}^B$ are idiosyncratic shocks.

We allow idiosyncratic shocks $\epsilon_{jt}^G$, $\epsilon_{jt}^B$, $\epsilon_{jt}^M$ and $\epsilon_{jt}^B$ to be correlated with one another to capture the simultaneity in effort decisions and common unexpected market conditions that affect all acquisition and maintenance outcomes. For example, a medical condition that prevents $j$ from working hard in period $t$ would affect all the acquisition and maintenance shocks.

### 4.6. State Transitions

Among the state variables in Table 2, tenure; and the amount of outstanding loans in total or by type evolve deterministically as follows:

$$\tau_{jt+1} = \tau_{jt} + 1,$$

$$O_{jt+1} = O_{jt} + N_{jt} - E_{jt},$$

$$O_{jt+1}^G = O_{jt}^G + N_{jt}^G - E_{jt}^G,$$

$$O_{jt+1}^B = O_{jt}^B + N_{jt}^B - E_{jt}^B,$$

where $N_{jt}$ is the amount of loans acquired loans by salesperson $j$ in period $t$ ($N_{jt}^G$ for good loans and $N_{jt}^B$ for bad loans).

Acquisition quota $Q_{jt+1}$ is a function of the amount of outstanding loans in period $t + 1$ ($O_{jt+1}$), acquisition quota in period $t$ ($Q_{jt}$) and the unobserved market condition in period

---

\[17\] More precisely, we can write the outcome equations as follows, where $p^G$ is the probability of a loan being a good type in population:

$$N_{jt}^G = p_{jt}^G e_{jt}^A(s_{jt}^A; s_{jt}^A; \lambda_{jt}^A) + f(X_{jt}; \beta_{jt}^A) + \epsilon_{jt}^A,$$

$$N_{jt}^B = (1 - p_{jt}^G) e_{jt}^A(s_{jt}^A; s_{jt}^A; \lambda_{jt}^A) + f(X_{jt}; \beta_{jt}^A) + \epsilon_{jt}^B,$$

where $p_{jt}^G$ is the fraction of good loans in the population, which can vary by salesperson $j$’s branch.
\[ Q_{jt+1} = g(O_{jt+1}, Q_{jt}, z_{t+1}; \phi) + \nu_{jt+1}, \]

where \( z_{t+1} \) represents period fixed effects.

### 4.7. Flow Utility Function

A salesperson’s flow utility is determined by her expected bonus minus the cost of effort. Salesperson \( j \) earns bonus \( B(N_{jt}, R_{jt}) \) based on acquisition and maintenance performance outcomes, where \( N_{jt} = N^G_{jt} + N^B_{jt} \) and \( R_{jt} = R^G_{jt} + R^B_{jt} \) and incurs cost \( C(e_{jt}) \), where \( e_{jt} = \{e^A_{jt}, e^B_{jt}, e^M_{jt}, e^M_{jt}\} \) if the salesperson has private information and \( e_{jt} = \{e^A_{jt}, e^M_{jt}\} \) otherwise. The utility function for period \( t \) is defined by the following:

\[
U(e_{jt}, N_{jt}, R_{jt}; \Gamma, \Theta_j) = E\left[B(N_{jt}, R_{jt}; \Gamma)\right] - C(e_{jt}; \Theta_j),
\]

where the bonus is computed following the firm’s compensation plan as \( B(N_{jt}, R_{jt}; \Gamma) = \left(\frac{N_{jt}}{Q_{jt}}\right)^* g\left(\frac{R_{jt}}{Q_{jt}}; \gamma\right) \). We specify the effort cost function for the salesperson with private information as follows.

\[
C(e_{jt}; \Theta) = \theta^C \left[ e^A_{jt} + \theta^B e^A_{jt} \right] + \theta^M \left[ e^M_{jt} + \theta^B e^M_{jt} \right]^2,
\]

where \( \theta^C \) measures the relative magnitude of effort to (monetary) bonus, \( \theta^A_B \) is the parameter for acquiring bad loans relative to good loans, \( \theta^M \) is the parameter for maintenance effort relative to acquisition effort, \( \theta^M_B \) is the parameter for maintaining bad loans relative to good loans. We denote \( \Theta = \{\theta^C, \theta^A_B, \theta^M, \theta^M_B\} \). Note that if \( \theta^M \) is greater than 1, monitoring effort is costlier than acquisition effort.

### 4.8. Bellman Equation

A salesperson makes effort decisions in a dynamically optimal manner, and the effort decisions are chosen to maximize the expected discounted sum of utility given state variables \( S_{jt} \); compensation plan \( \Gamma \); state transition parameters \( \phi \); policy function parameters \( \beta \) and \( \lambda \); \( j \)’s belief in the probability of a loan being a good loan without private information \( p^G_{jt} \);
and the salesperson’s per-period utility function that depends on structural parameters $\Theta$. We represent the optimization problem as the following Bellman equation:

$$V(S; \Gamma, \phi, \beta, \lambda, p^G, \Theta) = \max_{e} \left[ U(e, S; p^G, \Theta) + \delta E \left[ V(S'; \Gamma, \phi, \beta, \lambda, p^G, \Theta) \right] \right],$$

where $\delta$ is a monthly discount factor, which we assume to be 0.99, and $S'$ is the state variables for the next period. The expectation is obtained with respect to the idiosyncratic shocks in each period and the probability of being transferred.

### 5. Estimation and Identification

We estimate the model using a two-step forward-simulation estimation method (Bajari et al. 2007). In the first step, we estimate the salesperson’s production function, which includes the salesperson’s effort policy functions with flexible mapping between states, actions and performance outcomes along with exogenous outcome shifters and production shocks. In the second step, we estimate the structural parameters using the moment inequalities, constructed based on the revealed preference that the optimal effort choices based on estimated effort policy functions gives higher payoff to the salesperson than efforts that deviate from the effort policy function.

We allow salespeople to be heterogeneous in their cost of customer acquisition and maintenance. The heterogeneity across salespeople is essential for our interest in studying job task allocation. The two-step approach is thus modified to accommodate unobserved salesperson heterogeneity using the EM-type algorithm in Arcidiacono and Miller (2011). We estimate the heterogeneous policy functions and obtain each salesperson’s probability of belonging to one of the (latent) discrete segments in the first step. We then estimate the structural parameters in the second stage by segment.

There are two further challenges in the estimation of our model. First, with multitasking (and four outcomes in our application), there are far more state variables that link to outcome variables, making it even more challenging than in the single tasking applications to estimate flexible mappings between states and effort in the effort policy function of the first step. It is not straightforward to determine the functional form \textit{a priori} due to the large number of state variables in this setting. Moreover, semiparametric or nonparametric estimation typically faces a severe curse-of-dimensionality problem with many covariates. Hence, we use a machine learning method that allows high-dimensional nonparametric
estimation yet avoids over-fitting. Specifically, we use Random Forest to estimate the first-stage policy functions, and use cross-sample fitting to avoid over-fitting. See discussions about cross-sample fitting in Newey and Robins (2018) and Athey and Imbens (2016) for tree-based estimation. Note that the first-step of this two-step approach is purely a prediction exercise.

Second, a salesperson with private information makes separate effort decisions for ex ante good loans and bad loans. However, the loan type (ex ante profitability) conditional on public information is not directly observed by researchers. Hence, we must infer the loan type from observed ex post realized profitability, controlling for the influence of the salesperson’s behavior and other exogenous factors. We will explain how we make inference on loan type in Step 1a below, followed by the policy function estimation as shown in Step 1b of the first stage. We then explain Step 2 in Section 5.3.

5.1. Step 1a: Loan Type Inference
In this step, we infer loan type (i.e., ex ante loan profitability) from ex post loan profitability, or realized Internal Rate of Return (IRR). Since the salesperson can affect ex post loan profitability through a loan cycle, the ex ante profitability is not directly observed. Hence, the salesperson factors such as salesperson segments (e.g., if a salesperson is more efficient at loan acquisition and maintenance) and salesperson states (e.g., how many loans to collect in this period) should be controlled to infer ex ante loan type. We do so in the following steps.

5.1.1. Mapping between observables and loan profitability We first model Internal Rate of Return of loan $i$ ($IRR_i$), which represents ex post loan profitability, as a flexible function of observable and unobservable characteristics as follows:

$$IRR_i = f(L_i, S_j(i), State_{j(i)t...T(i)}) + u_i,$$

where $L_i$ is the vector of loan/borrower characteristics of loan $i$, $S_j(i)$ is the latent segment of salesperson $j$ who acquires loan $i$, and $State_{j(i)t...T(i)}$ includes salesperson characteristics and compensation states during the loan cycle, from the acquisition period $t$ until the maturity

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18 Recent papers by Chernozhukov et al. (2018b) and Semenova (2018) consider the estimation of the dynamic discrete choice models where the first stage policy function estimation is done with machine learning methods. However, such methods are not yet readily applicable for continuous-choice dynamic models such as ours.

19 In the case of multiple IRRs, we choose the rate closer to the loan’s interest rate.
Table OA2 in the online appendix provides summary statistics of these explanatory variables. We use the random forest algorithm to estimate the flexible function \( f(\cdot) \), which helps us avoid making an assumption on the functional form of \( f(\cdot) \). Since \( f(\cdot) \) is an equilibrium object, it is essential to allow a nonparametric function. We are thus able to capture the nonlinear relationship, particularly between \( \text{State}_{j(i) \ldots T(i)} \) and \( \text{IRR}_i \).

We must handle two empirical challenges in estimating equation (7): unobservability of \( S_{j(i)} \) and endogeneity of \( \text{State}_{j(i) \ldots T(i)} \). First, salespeople segment \( S_{j(i)} \) is not directly observed in the data. Hence, we estimate the salesperson segment as a latent class with EM algorithm, and we embed the loan type classification into the EM algorithm. More precisely, we iteratively conduct the loan classification step (Step 1a) and the heterogeneous policy function estimation step (Step 1b) until both steps converge. We will explain the details following Section 5.2.

Second, although salesperson characteristics and time-varying compensation states \( \text{State}_{j(i) \ldots T(i)} \) are observed in the data, unobserved factors (e.g., loan type) may affect both \( \text{State}_{j(i) \ldots T(i)} \) and \( \text{IRR}_i \) in equation (7), which may bias our inference of \( \text{ex ante} \) loan profitability. To handle the endogeneity issue, we instrument \( \text{State}_{j(i) \ldots T(i)} \) with \( Z_{j(i) \ldots T(i)} \), which affect salesperson compensation states, but do not affect the return of loan \( i \). The instruments include (i) salesperson \( j \)'s transfer status, (ii) the average IRR of the other loans acquired by salesperson \( j \) in period \( t \), and (iii) the average IRR of other loans maintained by salesperson \( j \) in period \( t \). Such variables affect the compensation states because they are determined by the aggregate profitability of loans in \( j \)'s portfolio, but does not directly affect \( \text{IRR}_i \), which is solely determined by loan \( i \)'s profitability conditional on observables. In particular, we first regress \( \text{State}_{j(i) \ldots T(i)} \) on \( Z_{j(i) \ldots T(i)} \) by OLS, and then plug the predicted value \( \hat{\text{State}}_{j(i) \ldots T(i)} \) into equation (7) to estimate \( f(\cdot) \) as in 2SLS.

When training the random forest algorithm, we make use of the information from 60,970 loans, for which we do not observe any missing values. We hold out 30\% of the observations for the test data and find that 1,000 trees with 15 predictors give the best prediction with the lowest mean square error for the test data. We report the importance of each variable in the online appendix.

\(^{20}\)The random forest algorithm constructs multiple decision trees to train the data, and it verifies the fit through cross-validation to find the optimal number of trees, and the optimal number of variables used to grow each tree.
5.1.2. Predicting \textit{ex ante} IRR  
To predict \textit{ex ante} profitability, we control for salesperson factors, such as salesperson segment $S_{j(i)}$ and her characteristics/states $\text{State}_{j(i)t...T(i)}$ (e.g., how many loans are to be collected by $j$ on average from period $t$ to $T$, how well $j$’s existing loans are being repaid on average from period $t$ to $T$), that shift the salesperson’s maintenance behaviors during the cycle of loan $i$ and eventually affects \textit{ex post} IRR of loan $i$.\footnote{A segment of salespeople who are more efficient at the maintenance task would do more monitoring than the other segment. \textit{Kim et al. (2019)} show how compensation states can affect the maintenance behavior of salesperson $j$ on loan $i$. A salesperson under high maintenance pressure during a loan cycle (e.g., a salesperson who could not collect loans, and thus received low maintenance index during a loan cycle) would exert more effort to monitor loans than the one under low maintenance pressure.} More specifically, we predict the \textit{ex ante} IRR ($\hat{IRR}_i$) with the following specification,

$$\hat{IRR}_i = \hat{f}(L_i, \tilde{S}_{j(i)}, \tilde{\text{State}}_{j(i)})$$

where $L_i$ is loan characteristic of loan $i$, $\tilde{S}_{j(i)}$ is the fixed effect for salesperson segment and $\tilde{\text{State}}_{j(i)t...T(i)}$ is the average compensation states of salesperson $j$ across all loans/periods.

We can control for the segment fixed effect in the iterative process between Step 1a and Step 1b.\footnote{After we compute $\hat{IRR}_i$ of the 60,970 loans, the remaining 39,280 loans, not included in the model due to missing predictors, are matched to one of the predicted 60,970 loans in the model by propensity score matching. We measure the similarity between the excluded loans and the included loans, in terms of the value of the loan characteristics and the salesperson characteristics/states. The similarity of the predictors is weighted by the variable importance in Figure OA1 in the online appendix to obtain propensity score. We plug in $\hat{IRR}_{ijt}$ of a matched loan to each of the 39,280 loans.}

Note that our goal here is to predict \textit{ex ante} loan profitability, which is the loan’s original profitability in the absence of active interventions by salespeople. For that purpose, we choose to set $\text{State}_{j(i)t...T(i)}$ at the average compensation states of salesperson $j$. The idea behind this approach is that the salesperson will not feel too much pressure to collect loans nor be too lax so that the borrower’s behavior is not distorted in any way by the salespeople.\footnote{Suppose, alternatively, that a salesperson whose loans tend not to be repaid at all (i.e., very low average maintenance index during loan cycle) might expect that she cannot earn maintenance incentive regardless of his effort and thus gives up making any effort. Then the return of each loan that she manages should be low. Similarly, a salesperson whose loans turn out to be collected too well (i.e., very high average maintenance index during loan cycle) would not exert costly effort, believing that the customers will repay the loans anyway. Her $IRR_i$ may also be low as well. The average $\text{State}$ does not generate such distortions.}

5.1.3. Classification of Loans  
Loan $i$ is classified into a good loan (i.e., a profitable, but harder-to-acquire loan) if $\hat{IRR}_i$ is greater than the cost of capital, which we define as the minimum interest rate of all loans ($42\%$ yearly interest rate), representing the minimum
to achieve from fully repaid loans, and a bad loan (i.e., an unprofitable, but easier-to-acquire loan) otherwise. Based on this classification rule, good loans account for 67% of the all loans in the data.\footnote{To check the robustness of our results in terms of the threshold to classify good and bad loans, we attempted sensitivity analyses by changing the rule for classification. We find that our classification results do not change much. For example, the threshold of good and bad loans based on the minimum interest rate of loans at each branch classifies 69% of all loans of the good type.}

After classifying each loan into either good or bad type, we aggregate the amount of acquired or repaid loans by loan type, for each salesperson in each period to create four state variables: the amount of new good loans ($N^G_{jt}$), that of new bad loans ($N^B_{jt}$), that of repaid good loans ($R^G_{jt}$) and that of repaid bad loans ($R^B_{jt}$).

### 5.2. Step 1b: Heterogeneous Production Function Estimation

Using the constructed state variables in Step 1a, we estimate the production functions in equations (1) and (2), which includes the salesperson’s effort policy functions. Rewriting the equation as follows:

\begin{align}
N^\omega_{jt} &= \epsilon^{A\omega}_{jt} (S_{jt}; \lambda^{A\omega}) + f(X_{jt}; \beta^{A\omega}) + \epsilon^{A\omega}_{jt}, \\
R^\omega_{jt} &= \epsilon^{M\omega}_{jt} (S_{jt}; \lambda^{M\omega}) + f(X_{jt}; \beta^{M\omega}) + \epsilon^{M\omega}_{jt},
\end{align}

where $\omega \in \{G, B\}$. As discussed above, since a multitasking salesperson makes simultaneous decisions on acquisition and maintenance, each effort function can be written as a function of all state variables as follows:\footnote{We do not explicitly model the limited total time/resource allocated by salesperson $j$ among multiple tasks, because it is difficult to assume that all salespeople spend an equal amount of time at work. However, modeling that acquisition efforts and maintenance efforts affect each other handles cases in which salespeople face the allocation problem.}

\begin{align*}
\epsilon^{T\omega}_{jt} (S_{jt}) &\equiv \epsilon^{T\omega}_{jt} (s^{AG}_{jt}, s^{AB}_{jt}, s^{MG}_{jt}, s^{MB}_{jt}),
\end{align*}

where $T \in \{A, M\}$ denotes either acquisition or maintenance and $\omega \in \{G, B\}$ denotes loan type. In equation (8), the exogenous shifters $X_{jt}$ include branch-level average acquisition quota $Q^b_t$; and the interaction between the salesperson tenure $\tau_{jt}$ and $Q^b_t$. The average acquisition quota in each branch captures the market condition, and the interaction with tenure is added to account for the differential impact of market condition for experienced/inexperienced salespeople. We specify $f(\cdot)$ as a linear function, i.e., $f(X_{jt}; \beta^{T\omega}) = X'_{jt} \beta^{T\omega}$. Lastly, the four-dimensional shocks $(\epsilon^{AG}_{jt}, \epsilon^{AB}_{jt}, \epsilon^{MG}_{jt}, \epsilon^{MB}_{jt})$ follow a Multivariate Normal distribution with mean 0 and covariance matrix $\Sigma$. We allow shocks to be correlated
with one another for the same salesperson in the same period, but i.i.d across salespeople or across periods.

To semiparametrically estimate equation (8), we use the backfitting algorithm (e.g., Buja et al. (1989) and Bickel et al. (2005)). The key idea is to estimate the additive components separately. The method iteratively solves for \( \hat{e}_{jt} \) and \( \left( \hat{\beta}, \hat{\Sigma} \right) \) by replacing the conditional expectation of the partial residuals at each stage as follows.

1. Initialize \( \hat{\beta}^{AG}, \hat{\beta}^{AB}, \hat{\beta}^{MG}, \hat{\beta}^{MB} \) and \( \hat{\Sigma} \).
2. Estimate \( \hat{\lambda}^{AG}, \hat{\lambda}^{AB}, \hat{\lambda}^{MG} \) and \( \hat{\lambda}^{MB} \) from the following moment condition:

\[
E \left( \begin{bmatrix}
N^G_{jt} - f(X^G_{jt}, \hat{\beta}^{AG}) \\
N^B_{jt} - f(X^B_{jt}, \hat{\beta}^{AB}) \\
R^G_{jt} - f(X^G_{jt}, \hat{\beta}^{MG}) \\
R^B_{jt} - f(X^B_{jt}, \hat{\beta}^{MB})
\end{bmatrix} \mid S_{jt} \right) = \begin{bmatrix}
\hat{\epsilon}^{AG}_{jt}(S_{jt}; \hat{\lambda}^{AG}) \\
\hat{\epsilon}^{AB}_{jt}(S_{jt}; \hat{\lambda}^{AB}) \\
\hat{\epsilon}^{MG}_{jt}(S_{jt}; \hat{\lambda}^{MG}) \\
\hat{\epsilon}^{MB}_{jt}(S_{jt}; \hat{\lambda}^{MB})
\end{bmatrix},
\tag{9}
\]

3. Predict \( \hat{\epsilon}^{AG}_{jt}(S_{jt}; \hat{\lambda}^{AG}), \hat{\epsilon}^{AB}_{jt}(S_{jt}; \hat{\lambda}^{AB}), \hat{\epsilon}^{MG}_{jt}(S_{jt}; \hat{\lambda}^{MG}) \) and \( \hat{\epsilon}^{MB}_{jt}(S_{jt}; \hat{\lambda}^{MB}) \), based on the estimates of \( \hat{\lambda}^{AG}, \hat{\lambda}^{AB}, \hat{\lambda}^{MG} \) and \( \hat{\lambda}^{MB} \).
4. Estimate \( \left( \hat{\beta}^{AG}, \hat{\beta}^{AB}, \hat{\beta}^{MG}, \hat{\beta}^{MB}, \hat{\Sigma} \right) \) in \( f(\cdot) \) functions by MLE constructed by \( \epsilon_{jt} = (\epsilon^{AG}_{jt}, \epsilon^{AB}_{jt}, \epsilon^{MG}_{jt}, \epsilon^{MB}_{jt}) \), which follow a Multinomial Normal distribution.

\[
(\hat{\beta}^{AG}, \hat{\beta}^{AB}, \hat{\beta}^{MG}, \hat{\beta}^{MB}, \hat{\Sigma}) = \arg \max L \left( \begin{bmatrix}
N^G_{jt} - \hat{f}(X^G_{jt}) - \hat{\epsilon}^{AG}_{jt}(S_{jt}) \\
N^B_{jt} - \hat{f}(X^B_{jt}) - \hat{\epsilon}^{AB}_{jt}(S_{jt}) \\
R^G_{jt} - \hat{f}(X^G_{jt}) - \hat{\epsilon}^{MG}_{jt}(S_{jt}) \\
R^B_{jt} - \hat{f}(X^B_{jt}) - \hat{\epsilon}^{MB}_{jt}(S_{jt})
\end{bmatrix} \right),
\]

where \( L(\cdot) \) is the log-likelihood function of \( \epsilon_{jt} \), i.e., \( \sum_{j} \sum_{t} \log \phi(\epsilon_{jt}) \) with the density function of the Multinomial Normal distribution.

5. Iterate 2–4 until convergence.

In Step 2, we make use of a machine learning approach to allow for flexible effort policy functions, where \( N^G_{jt} - \hat{f}(X^G_{jt}) \) is the outcome for prediction and \( S_{jt} \) is the explanatory variables. Note that the left-hand side variables are all scalar variables given \( \beta \)'s. It is important not to make a restrictive assumption on the functional form, which might lead to biased structural parameter estimates. Specifically, we use the random forest algorithm due to its high predictive power and flexibility for the nonparametric estimation. Moreover, we combine the algorithm with cross-sample fitting to eliminate overfitting and ensure
the consistency of the estimator under a high-dimensional effort function (Chernozhukov et al. 2018a), motivated by Newey and Powell (2003). To do so, we randomly divide the observations into the main and auxiliary samples, each of which takes up 50% of the data; we obtain the estimates only from the main sample only and those from the auxiliary sample only; and we then average the results across the samples.

**Incorporating unobserved heterogeneity** We incorporate salesperson unobserved heterogeneity through persistent latent segments and estimate heterogeneous policy functions using the Expectation-Maximization (EM) algorithm developed in Arcidiacono and Jones (2003) and Arcidiacono and Miller (2011). A latent segment is denoted by $k \in \{1, 2, \ldots, K\}$ ($K$ is the number of discrete segments) and we estimate segment-level efforts $(e^A_G, e^A_B, e^M_G, e^M_B)$ and a covariance matrix $\Sigma_k$ in this step. Following the application in Chung et al. (2013), we compute the log-likelihood of simultaneously observing salesperson $j$’s acquisition and maintenance performance $(N^G_{jt}, N^B_{jt}, R^G_{jt}, R^B_{jt})$ given segment-level parameters and the persistent segment $k$ to which salesperson $j$ belongs:

$$L_{jkt} = L(N^G_{jt}, N^B_{jt}, R^G_{jt}, R^B_{jt} | k; e_k, \beta_k, \Sigma_k),$$

where $L(\cdot)$ is the log-likelihood defined in step 4 of the backfitting algorithm described in the previous step (with a little abuse of notation). The full-information log-likelihood, weighted by the probability of salesperson $j$ being in segment $k$ ($q_{jk}$) is as follows:

$$\sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T q_{jk} L_{jkt},$$

where

$$q_{jk} = Pr(k | N^G_{jt}, N^B_{jt}, R^G_{jt}, R^B_{jt}; e, \beta, \Sigma, p) = \frac{p_k \left( \prod_{t=1}^T L_{jkt} \right)}{\sum_{k=1}^K p_k \left( \prod_{t=1}^T L_{jkt} \right)}$$

and $p_k$ is the fraction of segment $k$.

The EM algorithm is described as follows for the $(m+1)$-th iteration:

1. Compute $q_{jk}^{(m+1)}$ using equation (11) with $e^{(m)}, \beta^{(m)}, \Sigma^{(m)}$ and $p^{(m)}$.
2. Obtain $e^{(m+1)}, \beta^{(m+1)}$ and $\Sigma^{(m+1)}$ by maximizing the full information maximum likelihood, weighted by $q_{jk}^{(m+1)}$ in equation (10).
3. Update $p^{(m+1)}$ by taking the average of $q_{jk}^{(m+1)}$.

We iterate step 1 – 3 until convergence. The initial values are estimates of $e, \beta$ and $\Sigma$ without unobserved heterogeneity, and random size $p$ that sums up to 1.
Combining Step 1a and Step 1b We now explain how to combine the loan type inference step (Step 1a) and the heterogeneous production function estimation step (Step 1b). Since loan types and latent segments are both unobserved in the data, we must iteratively execute Step 1a and Step 1b, starting from the initial guess of the latent segment distribution (i.e., 50% for each segment). Given the estimate of the loan type distribution obtained in Step 1a, we can estimate the latent segment distribution in Step 1b. The procedure terminates if both the loan type distribution and the latent segment distribution converge, respectively. The iterative procedure between Step 1a and Step 1b enables us to jointly estimate loan type and salesperson segment, and to control for salesperson segment \(S_{j(i)}\) in the loan type inference.\(^{26}\)

5.3. Step 2: Structural Parameter Estimation

The second step estimates the structural parameters \(\Theta_k\), consisting of the parameters related to the total effort \((\theta_k)\), the acquisition effort for bad loans relative to good loans \((\theta_{k}^{AB})\), the maintenance effort relative to acquisition effort \((\theta_{k}^{M})\), and the maintenance effort for bad loans relative to good loans \((\theta_{k}^{MB})\) for each salesperson segment \(k\). We estimate the structural parameters with forward-simulation as in Bajari et al. (2007). We first recover the value function under the optimal policy (the estimated effort policy function), denoted by \(\hat{V}\), and then calculate the counterfactual value function under the policies

\(^{26}\) We iterate between Step 1a and Step 1b twice and find that the estimates converge.
that deviate from the optimal policy, denote by $\tilde{V}$.

Lastly, the moment inequalities can be constructed from the difference between two value functions. Segment-level structural parameters are estimated by the minimum distance estimator of the difference between

$$\hat{\Theta}_k = \arg \min_{\Theta_k} \left[ \min \left\{ \hat{V}(s|k; e_k, \hat{\beta}_k, \Sigma_k, \phi, \Theta_k) - \tilde{V}(s|k; \tilde{e}_k, \tilde{\beta}_k, \tilde{\Sigma}_k, \phi, \tilde{\Theta}_k), 0 \right\} \right]^2,$$

where $e_k$ is the estimated optimal policy and $\tilde{e}_k$ is the deviated policy. Bootstrapped standard errors are calculated based on 500 randomly selected samples.

5.4. Identification

We now discuss identification of our structural model. There are several points that warrant discussion.

First, the existence of continuing officers’ private information is not directly observed. Based on the findings of Kim et al. (2019), we take advantage of the random transfers that eliminate the salesperson’s private information about customers. That is, the random transfers allow us to identify the existence of private information about customers from continuing salespeople. Hence, we can consider identification of the model of salespeople with private information and the one without private information separately by considering the salespeople who are not randomly transferred and those who are randomly transferred.

Second, to identify the acquisition and the maintenance effort policy functions, we borrow the arguments in the existing salesforce compensation papers (e.g., Misra and Nair 2011, Chung et al. 2013). A key identification challenge is the fact that a salesperson’s multi-dimensional efforts are not observed. Following the existing papers, we assume that realized outcomes are a function of demand shifters, a deterministic function of effort, and additive sales shocks. Given this structure, conditional on observable demand shifters, $X_{jt}^A$, the variation in $N_{jt}$ and the variation in $S_{jt}$ allow us to separately identify the effort function $e_{jt}^A(\cdot)$ and idiosyncratic acquisition sales shocks. We can make a similar argument for maintenance effort policy function. Since we do not observe effort, we normalize the effect

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27 The deviation from the optimal strategy is obtained by adding a random shock drawn from a Normal distribution with standard errors of 0.01. We do forward-simulation over 14 periods for 100 simulations to calculate $\tilde{V}$. The details are explained in the online appendix.

28 Again, we assume that transferred salespeople obtain complete information about borrowers (i.e., become continuing salespeople) from their second month at the new branch. We examine the robustness of our results based on this assumption.
of effort on outcome while we allow flexible relationships between states $S_{jt}$ and efforts $e_{jt}^A$ and $e_{jt}^M$. Given that the effort functions are identified, the effects of exogenous demand shifters, $f(X; \beta^A)$ and $f(X; \beta^M)$ are identified from the variation in $X_{jt}$ conditional on $S_{jt}$. The covariance in outcomes $N_{jt}$ and $R_{jt}$ conditional on states and exogenous shifters, $S_{jt}$ and $X_{jt}$, allows us to identify the covariance of shocks $\Sigma$.

Third, similar to Misra and Nair (2011) and Chung et al. (2013), the parameters in the effort cost function, $\Theta$, are identified from the intertemporal linkage of states, efforts, and outcomes. More formally, given the outcome functions identified and our assumption on the utility function from the bonus, the first-order condition of the salesperson’s optimization problem pins down the effort cost parameters.

6. Results

We first report the results of the first stage estimation of loan officer production functions. Then, we report the second stage estimates of the parameters of the structural model.

6.1. First Stage Estimation: Loan officer production functions

We allow for discrete segment heterogeneity in loan officer production functions and estimate them for each each segment that have two components: an effort policy function and a function of exogenous production shifters as well as shocks.

We find that a two segment model—one with a segment share of 68% and other with 32%, best fits the data. We next report the estimates of the exogenous production shifters on the four loan officer outcomes by segment in Table 3. The first two panels show the impact of exogenous shifters on acquisition performance for good loans and bad loans respectively. Not surprisingly, acquisitions are greater in branches with higher quotas, reflecting their greater market size. Interestingly, experience (tenure) reduces the incremental impact on good loans; however, it increases the incremental impact of bad loans, suggesting that experienced salespeople are better at using private information to acquire bad loans at the margin.

The bottom two panels of the table present the estimates in maintenance performance functions for good and bad loans respectively. The results indicate that as the average acquisition quota increases, repayment performance deteriorates. This is understandable as salespeople must exert more effort in loan acquisition when there are larger quotas and thus focus less on loan collection. As expected, experience helps salespeople to improve maintenance.
Table 3 Loan Officer Outcome Functions: Exogenous Demand Shifters in $f(\cdot)$

<table>
<thead>
<tr>
<th>Segment Share</th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>68 %</td>
<td>32 %</td>
</tr>
</tbody>
</table>

### Acquisition of Good Loans

<table>
<thead>
<tr>
<th></th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Quota (branch)</td>
<td>44.68 (0.170)</td>
<td>38.15 (0.096)</td>
</tr>
<tr>
<td>Tenure * Average Quota (branch)</td>
<td>-10.44 (0.040)</td>
<td>-9.27 (0.022)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.81 (0.033)</td>
<td>-6.92 (0.033)</td>
</tr>
</tbody>
</table>

### Acquisition of Bad Loans

<table>
<thead>
<tr>
<th></th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Quota (branch)</td>
<td>11.94 (0.053)</td>
<td>9.38 (0.042)</td>
</tr>
<tr>
<td>Tenure * Average Quota (branch)</td>
<td>4.32 (0.016)</td>
<td>4.91 (0.014)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-8.55 (0.036)</td>
<td>-6.22 (0.031)</td>
</tr>
</tbody>
</table>

### Maintenance of Good Loans

<table>
<thead>
<tr>
<th></th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Quota (branch)</td>
<td>-1.28 (0.004)</td>
<td>-0.45 (0.011)</td>
</tr>
<tr>
<td>Tenure * Average Quota (branch)</td>
<td>1.44 (0.005)</td>
<td>1.17 (0.004)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-1.78 (0.007)</td>
<td>-1.57 (0.005)</td>
</tr>
</tbody>
</table>

### Maintenance of Bad Loans

<table>
<thead>
<tr>
<th></th>
<th>Segment 1</th>
<th>Segment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Quota (branch)</td>
<td>-33.04 (0.138)</td>
<td>-33.21 (0.071)</td>
</tr>
<tr>
<td>Tenure * Average Quota (branch)</td>
<td>0.92 (0.004)</td>
<td>0.95 (0.003)</td>
</tr>
<tr>
<td>Intercept</td>
<td>3.07 (0.013)</td>
<td>3.07 (0.008)</td>
</tr>
</tbody>
</table>

Note: Standard errors estimated based on sample standard deviation are in the parentheses.

The estimates of the nonparametric effort policy functions of the two segments are not easy to interpret. We therefore highlight some illustrative features of the acquisition and maintenance effort policy functions. Figure 5 shows the four types of effort by segment against the fraction of unpaid loans in period $t - 1$—a proxy of the quality of the loan portfolio of the officer—a relevant state variable. Note that the higher the fraction of unpaid loans, the lower the quality of the current loan portfolio and the more difficult it is to perform well on the maintenance metric. The first and second subplots in Figure 5 show the acquisition effort on good and bad loans, respectively, while the third and fourth subplots show the corresponding maintenance effort.\(^{29}\)

A few aspects stand out from the plots. Segment 2 expends more effort on good loans relative to Segment 1 whereas Segment 1 expends more effort than Segment 2 on bad loans. This suggests that the moral hazard issues will be greater with Segment 1 than

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29 To draw each subplot in Figure 5, we first calculate each segment’s effort levels at each point of fraction of unpaid loans using estimated effort functions $e_{kt}^{T_{j}, S_{jt}; \lambda^{T_{w}}}$ where $T \in \{A, M\}$ and $w \in \{G, B\}$. To control for the effect of the other state variables used to obtain the effort levels (e.g., acquisition quota), the average values of such state variables at each point of fraction of unpaid loans by segment are used as inputs in the effort functions. Next, we construct a curve for each segment that has the best fit for the calculated effort levels against the fraction of unpaid loans. The x-axis, which indicates the fraction of unpaid loans is truncated at 0.2, because salespeople cannot earn any maintenance bonus at all beyond the point 0.125; thus the fraction rarely exceeds 0.2.
with Segment 2. In general, the salespeople of both segments put more acquisition effort when the quality of the loan portfolio is good; however, they reduce acquisition effort and increase maintenance effort, as shown in the maintenance plots when the portfolio quality is bad. Even more interestingly, the maintenance effort on bad loans increase when the fraction of loans is higher than 0.1, reflecting the highly nonlinear compensation schedule, where the maintenance points \((M)\) drop to zero at approximately 12.5\%, and therefore the salespeople are incentivized to shift effort more to maintenance and even try to recover bad loans.

**Figure 5  Effort Policy by Segment depending on Fraction of Unpaid Loans in the Previous Period**

(a) Effort to Acquire Good Loans  
(b) Effort to Acquire Bad Loans  
(c) Effort to Maintain Good Loans  
(d) Effort to Maintain Bad Loans

6.2. Structural Cost Parameter Estimates

Estimates of the structural cost parameters are reported in Table 4. As indicated by the higher \(\theta_k^C\), Segment 2 has greater disutility from effort than Segment 1; thus, Segment
1 is overall more productive. The estimate of $\theta_{AB}^k$, for Segment 1 shows that Segment 1 finds the effort to acquire bad loans is only approximately 15% of the cost of acquiring a good loan. Thus, although Segment 1 is more productive, the salesperson will use private information to more aggressively acquire bad loans. By contrast, the estimate of $\theta_{AB}^k$ for Segment 2 suggests that the Segment 2 salesperson finds it equally costly to acquire good and bad loans; hence, although it is less productive, there is less danger that Segment 2 disproportionately allocates effort to acquire bad loans.

In terms of the costs of maintenance effort, the estimate of $\theta_{M}^k$ shows that Segment 1 finds it roughly the same level of effort cost to acquisition and maintenance. Similarly, the estimate of $\theta_{MB}^k$ implies that the maintenance cost of bad loans is similar to that of good loans for Segment 1, whereas it is relatively more costly for Segment 2. Thus Segment 2 is less likely to acquire bad loans due to higher acquisition costs, and it is also more likely to spend effort in collecting the good loans it acquires.

Based on these findings, we call Segment 1 as the “hunter” segment, which is made up of salespeople who are not only relatively good at acquiring new customers, but who are also likely to acquire bad customers. In contrast, we call Segment 2 as the “farmer” segment, which is made up of salespeople who not only have a comparative advantage in collecting past loans (especially good loans), but who are also less likely to acquire bad loans in the first place.

We next use counterfactuals to investigate how the heterogeneity across segments has implications in designing job task allocations and incentive plans.

### Table 4  Structural Parameters

<table>
<thead>
<tr>
<th></th>
<th>Segment 1 (Hunter)</th>
<th>Segment 2 (Farmer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share: 68%</td>
<td>1.970 (0.016)</td>
<td>3.322 (0.025)</td>
</tr>
<tr>
<td>Relative Acquisition Cost of Bad Loans ($\theta_{AB}^k$)</td>
<td>0.146 (0.014)</td>
<td>0.965 (0.065)</td>
</tr>
<tr>
<td>Relative Cost of Maintenance Effort ($\theta_{M}^k$)</td>
<td>1.063 (0.008)</td>
<td>0.303 (0.037)</td>
</tr>
<tr>
<td>Relative Maintenance Cost of Bad Loans ($\theta_{MB}^k$)</td>
<td>0.964 (0.138)</td>
<td>2.968 (0.890)</td>
</tr>
</tbody>
</table>

Note: $C(e_{jt}, \Theta_j) = \theta_{CM}^j \left[ (e_{jt}^{AG} + \theta_{AB}^j e_{jt}^{AB}) + \theta_{M}^j (e_{jt}^{MG} + \theta_{MB}^j e_{jt}^{MB}) \right]^2$. 

7. Counterfactuals

We examine the main research questions through three counterfactual policy simulations. The first one investigates the question of job design, by comparing outcomes under a multitasking and specialization job design. Specifically, we assess outcomes when under multitasking where salespeople are responsible for both loan acquisition and maintenance tasks, relative to specialization where different salespeople are responsible for loan acquisition and maintenance. The second counterfactual investigates how under multitasking, performance along multiple tasks should be combined in linking performance to incentives. Specifically, we evaluate outcomes when performance on acquisition and maintenance tasks are combined multiplicatively or additively. The last counterfactual investigates the effect of transfers on performance through its impact on salesperson private information.

For each counterfactual outcome, we simulate a salesperson’s actions 500 times for each segment (“hunter” or “farmer”). To highlight the trade-off between efficiency and incentive alignment in the first two counterfactuals, we consider the case where the salesperson has private information, i.e., we do not allow for transfers in these counterfactuals. For the last counterfactual on private information, we compare outcomes when salespeople are never transferred to a setting where salespeople are transferred (and lose private information) in every period with a fixed probability.

7.1. Job Allocation Design

For the purposes of this counterfactual, we consider two polar cases of specialization and multitasking. To highlight the effects of task specialization, we assign the acquisition task to “hunters,” who are more effective at acquisition and the maintenance task to “farmers,” who are more effective at maintenance. In contrast, both segments are responsible for both acquisition and maintenance task in the multitasking case.

For multitasking, we use the same compensation plan used by the firm. For specialization, we solve the bank’s optimization problem to obtain the optimal $k^A$ and $k^M$ linking

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30 The hypothetical salesperson is based on the average characteristics of salespeople in each segment.
acquisition and maintenance performance to salesperson incentives as follows:\(^\text{31}\)

\[
\max_{k^A, k^M} E \left[ \sum_{t=1}^{\infty} \Pi_t (N_t, R_t) - k^A A_t - k^M M_t \right]
\]

s.t. \(N_t = N_t^G + N_t^B, \quad R_t = R_t^G + R_t^B,\)

\[
N_t^\omega = e_t^\omega + f(X_t; \beta^\omega) + \epsilon^\omega_t (\omega \in \{G, B\}),
\]

\[
R_t^\omega = e_t^M + h(X_t; \beta^M) + \epsilon^M_t (\omega \in \{G, B\}),
\]

\[
e^A* = \arg \max_{e^A} E \left[ \sum_{t=1}^{\infty} \delta^A_t (k^A A_t - C^H(e^A_t)) \right],
\]

\[
e^M* = \arg \max_{e^M} E \left[ \sum_{t=1}^{\infty} \delta^M_t (k^M M_t - C^F(e^M_t)) \right],
\]

where \(\Pi_t\) is the profits for the bank, \(C^H(\cdot)\) is the estimated effort cost function for the hunter segment and \(C^F(\cdot)\) is the estimated effort cost function for the farmer segment. Note that \(e^A = \{e^A_t\}_{t=1}^{\infty}, \quad e^M = \{e^M_t\}_{t=1}^{\infty},\) where \(e^A_t = \{e^{AG}_t, e^{AB}_t\}\) and \(e^M_t = \{e^{MG}_t, e^{MB}_t\}.\) The optimal linear compensation turns out to be \(k^A* = 0.5\) and \(k^M* = 0.75.\)

Table 5 reports the acquisition/maintenance performance of each type of loan and overall firm profits (Net Present Value - incentive payout to salespeople) under multitasking and specialization. Figure 6 reports three measures of loan performance under the two types of job design. Table 5 shows that hunters acquire more loans, but particularly more bad loans under the specialization scheme than under the multitasking. Similarly, farmers maintain more good loans under the specialization and only slightly fewer bad loans. These findings confirms the overall efficiency gain of the specialization design.

However, these efficiency gains are more than overwhelmed by moral hazard. Figure 6a further shows that hunters acquire significantly more bad loans under the specialization and the repayment probability is significantly lower as farmers are not good at collecting the bad loans (see Figure 6b). Overall, this leads to a 35% lower profit under specialization (see Figure 6c).

We elaborate further on how specialization hurts the firm, despite the efficiency gain in both segments. First, since hunters do not internalize the future consequences of acquiring bad loans, they exploit private information much more under the specialization and acquire

\(^{31}\) We restrict the incentive plan to be a linear function of acquisition and maintenance performance and search for the optimal parameters of the incentive plan using grid search. In the appendix, we report the profits under different values of \(k^A\) and \(k^M.\)
bad loans than they do under the multitasking. Second, since farmers are good at collecting good loans, but not good at collecting bad loans, most of the bad loans acquired by hunters are not collected. Together, this leads to a significant reduction in repayment and NPV.

Table 5  Profitability: Multitasking versus Specialization

<table>
<thead>
<tr>
<th>Job Design</th>
<th>Multi-tasking</th>
<th>Hunter</th>
<th>Farmer</th>
<th>Aggregate</th>
<th>Hunter</th>
<th>Farmer</th>
<th>Aggregate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition - Good</td>
<td>93.1</td>
<td>98.3</td>
<td>94.8</td>
<td>135.1</td>
<td>135.1</td>
<td></td>
<td>135.1</td>
</tr>
<tr>
<td>Acquisition - Bad</td>
<td>196.8</td>
<td>102.9</td>
<td>166.8</td>
<td>300.9</td>
<td>300.9</td>
<td></td>
<td>300.9</td>
</tr>
<tr>
<td>Maintenance - Good</td>
<td>79.5</td>
<td>81.6</td>
<td>80.2</td>
<td>95.9</td>
<td>95.9</td>
<td></td>
<td>95.9</td>
</tr>
<tr>
<td>Maintenance - Bad</td>
<td>115.4</td>
<td>78.8</td>
<td>103.7</td>
<td>111.3</td>
<td>111.3</td>
<td></td>
<td>111.3</td>
</tr>
<tr>
<td>Net Present Value (NPV)</td>
<td>470.6</td>
<td>424.7</td>
<td>455.9</td>
<td>372.7</td>
<td></td>
<td></td>
<td>372.7</td>
</tr>
<tr>
<td>Incentive Payout</td>
<td>63.8</td>
<td>66.0</td>
<td>63.8</td>
<td>80.4</td>
<td></td>
<td></td>
<td>80.4</td>
</tr>
<tr>
<td>Profit (NPV - Payout)</td>
<td>406.8</td>
<td>358.7</td>
<td>392.1</td>
<td>292.3</td>
<td></td>
<td></td>
<td>292.3</td>
</tr>
</tbody>
</table>

1) Multitasking Incentive Plan: $Bonus = A \times M$
2) Specialization Incentive Plan: $Bonus = 0.5A$ for Hunter and $Bonus = 0.75M$ for Farmer
3) Aggregate measures take account of share of hunters (68%) and that of farmers (32%) in the setting.
4) All values are in 1,000 pesos.
5) NPV is based on monthly interest rate of 1%.

While in this analysis we have focused on the polar cases of specialization and multitasking to generate insights into the tradeoff between efficiency and incentive alignment, we note that other variations in task allocation and compensation plans are feasible. For example, one could create a team structure, where performance is measured at the team level, but team members have specialized tasks. One can also vary other elements of the compensation plan such as acquisition and maintenance targets and how these targets evolve over time. While we consider the sensitivity of our insights to a few alternative
job allocation/incentive schemes in the appendix, we leave the full problem of optimal job design along all of these dimensions for future research.

7.2. Incentive Plan Design

Given that we find multitasking to be more profitable than specialization, we next explore the question of how to combine performance metrics based on multiple tasks in computing the incentive bonus. We consider the multiplicative structure used by the firm, i.e., $\text{Bonus} = A \times M$ as the benchmark and compare it against an additive structure, where $\text{Bonus} = wA + (2 - w)M$. After solving the bank’s optimization problem regarding $w$ similar to the problem in the previous subsection, we find that the optimal weight would satisfy $w^* = .5$ for this counterfactual.\(^{32}\)

In Table 6, we report the acquisition/maintenance performance of each segment of salespeople for good and bad loans; and firm profit considering Net Present Value (NPV) of loans and the incentive payout to salespeople. We find that under the additive scheme, the hunter segment acquires 6% more bad loans, and repayment is 6% lower. Thus, under the additive incentive scheme, hunters expend more effort on the loan acquisition task on which they have a comparative advantage, relative to loan collection. This leads to the total NPV of the hunters’ loans going down by 12% and the profitability after incentive payout going down by 13.8%. In Figure 7, we visually present the key results in terms of the repayment probability and profit of the loans acquired and collected by each segment of salespeople. For hunters, the repayment probability and the total profit are higher under the multiplicative scheme. This is consistent with the insight from MacDonald and Marx (2001) in that multiplicative incentive scheme can mitigate adverse specialization.

However, the results are reversed for farmers; repayment probability and NPV are higher with the additive scheme. As shown in Figure 7, the acquisition performance is 11.4% higher; further, loan collection is 14.5% higher as well. Thus, the NPV of the loans goes up by 18.3%, and the total profit after considering the incentive payout is 21.1% higher.

Since it is equally costly for farmers to acquire good and bad loans at the acquisition stage, more loan acquisition leads to roughly equal increases in good and bad loans. Since

\(^{32}\) We do a grid search over $w$ for the additive incentive scheme, $\text{Bonus} = wA + (2 - w)M$, where $w \in \{0.25, 0.5, ..., 1.75\}$ to find the profit-maximizing scheme within the additive incentive plan. We put the weight of 2 – $w$ to the maintenance points in order to normalize the bonus level. Since $w = 0.5$ generates the highest profit for the firm considering Net Present Value of loans and incentive payout to salespeople. As shown in Figure OA3, we report the result with $\text{Bonus} = 0.5A + 1.5M$ only in Table 6; however, the results are qualitatively identical for other values of $w$. 
farmers know they are not good at collecting bad loans later, under the additive scheme they reduce loan acquisition to reduce the number of bad loans in their portfolio. Nevertheless, the increased complementarity induced by multiplicative scheme requires the farmer segment to increase acquisition relative to collection, which leads to more bad loans and subsequent reduced repayment. Our insight that multiplicative incentive scheme can make the firm worse off under certain conditions is theoretically novel and contributes to a better understanding of the role of payoff complementarity in incentives. However, we note that in our setting, given that hunters account for a greater proportion of the salesforce at the firm, the total profits for the firm under the multiplicative incentive scheme is greater.

Again, while it is possible to consider more general compensation schemes than the linear additive incentive that we consider here, our main purpose here is to highlight how
multiplicative incentive schemes may hurt firms by inducing more-than-desired complementarities.\footnote{We consider an alternative scheme where hunters and farmers specialize on the acquisition and maintenance tasks respectively; however, hunters’ incentives are based on $A \times M$. The details are presented in the appendix. Overall, we leave the full characterization of the optimal incentive scheme design for future research.}

7.3. Job Transfers and Private Information

Our estimation results imply that private information is a double-edged sword: it can help salespeople acquire less risky loans and make better maintenance decisions; however, it can also lead to salesperson moral hazard to acquire less profitable, but easier-to-acquire customers (i.e., create incentive misalignment). The final counterfactual examines the role of the transfer policy in eliminating private information and how the policy affects firm’s profits.

We do so by simulating salesperson behavior using the estimated policy function when salespeople have private information (i.e., when they are not transferred) and the estimated policy function when they do not have private information (i.e., when they are transferred with 100% probability). Table 7 and Figure 8 describe salesperson performance and profitability when they do not have private information versus when they do. With private information, hunters abuse their knowledge to acquire more bad loans by 8.8% (Figure 8a), which are repaid less by 13.7% (Figure 8b), and generate lower profit by 3% (Figure 8c). By contrast, farmers take advantage of private information to be involved in fewer new bad loans by 5.2% (Figure 8a), selectively monitor and better collect loans by 2.8% (Figure 8b), and generate higher profit by 2% (Figure 8c). Overall, our simulation results suggest that the firm can improve profits by transferring hunters more frequently than farmers, instead of the current random policy, where all salespeople are equally likely to be transferred.\footnote{In our case, the incremental benefit of a more frequent transfer policy is limited. Hence, associated administrative costs might exceed the benefit of the more frequent transfers.}
Table 7  Profitability: Without versus With Private Information

<table>
<thead>
<tr>
<th></th>
<th>Hunter Private Information</th>
<th>Without Private Information</th>
<th>With Private Information</th>
<th>Aggregate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition - Good</td>
<td>93.1</td>
<td>98.3</td>
<td>94.8</td>
<td>Hunter</td>
</tr>
<tr>
<td>Acquisition - Bad</td>
<td>196.8</td>
<td>102.9</td>
<td>123.5</td>
<td>122.3</td>
</tr>
<tr>
<td>Maintenance - Good</td>
<td>79.5</td>
<td>81.6</td>
<td>80.2</td>
<td>79.3</td>
</tr>
<tr>
<td>Maintenance - Bad</td>
<td>115.4</td>
<td>78.8</td>
<td>103.7</td>
<td>89.7</td>
</tr>
<tr>
<td>Net Present Value (NPV)</td>
<td>470.6</td>
<td>424.7</td>
<td>455.9</td>
<td>450.5</td>
</tr>
<tr>
<td>Incentive Payout</td>
<td>63.2</td>
<td>65.9</td>
<td>63.8</td>
<td>55.5</td>
</tr>
<tr>
<td>Profit (NPV - Payout)</td>
<td>407.4</td>
<td>358.7</td>
<td>392.1</td>
<td>395.0</td>
</tr>
</tbody>
</table>

1) Aggregate measures take account of share of hunters (68%) and that of farmers (32%) in the setting.
2) All values are in 1,000 pesos.
3) NPV is based on monthly interest rate of 1%.

Figure 8  Loan Performance: Without versus With Private Information

(a) Share of Bad Loans (%)  (b) Repayment Probability (%)  (c) Profit (1000 Pesos)

8. Conclusion

This paper develops a new structural model of multitasking that can have potential application in a wide range of literatures–including management, marketing, operations and organizational economics. The model allows for employee moral hazard by allowing employees to have private information about customers which affects their marginal cost of reaching performance goals that are misaligned with the firms’s objectives. We then use this structural model to study questions of job task allocation and incentive design for salespeople in the presence of complementarities between tasks (i.e., acquisition and maintenance) using the unique matched data of loan officer compensation and loan performance.

Our estimation results show that there are two segments of salespeople: hunters and farmers. The first segment is better at acquiring new customers, while the second segment is better at maintaining the relationship with existing customers. This heterogeneity across salespeople motivates us to study an alternative job task allocation design. In particular, we
consider the salesperson performance and profitability of the specialization job design, in
which the hunter salesperson is responsible only for acquisition and the farmer salesperson
is responsible only for monitoring.

Our simulation results show that the multitasking job design performs better under our
context. We then consider an alternative incentive design under multitasking, inspired by
a seminal paper by MacDonald and Marx (2001). Our findings suggest that the coun-
terfactual additive incentive scheme leads to adverse specialization of hunter salespeople
whereas the company’s multiplicative incentive scheme effectively disciplines both hunter
and farmer salespeople. Lastly, we evaluate the role of transfers that eliminate private
information. Such transfers are a double edged sword in that they reduce moral hazard and
adverse selection among “hunters,” but hurts the effectiveness of “farmers” in loan repay-
ment. Overall, given the larger size of the “hunter” segment, across-the-board transfers are
helpful to the firm.

The paper made several advances in the structural modeling of salesforce management
issues in extending the model to issues of job design and incentive design under multita-
ksing. However, there remain issues that we abstracted away or did not account for due to
a lack of relevance for our current application, which are potentially fertile areas of study
for future research. First, while we considered the extreme cases of specialization and mul-
titasking, we abstracted away from potential job designs involving teams where different
members are responsible for different tasks; however, the team overall is responsible for
the overall outcomes. Second, optimizing each component of the compensation plan, such
as how to set acquisition quotas or the functional form linking maintenance performance
to incentives is also beyond the scope of this paper. Third, while our application is for loan
officers in the banking sector and there are parallels with customer acquisition and reten-
tion tasks in customer relationship management settings, it would be useful to consider
an explicit application where salespeople are truly responsible for CRM. In such settings,
the customer maintenance tasks can have multiple components involving customer growth
and retention. Finally, Holmström and Milgrom (1991) discuss the accuracy and measura-
bility of performance metrics as critical in job and incentive designs. It would be useful to
consider multiple tasks where the accuracy of measurement might differ across tasks (e.g.,
sales is more precisely measured than customer satisfaction) and how these differences
impact job and incentive design.
References


Kim, Sudhir and Uetake: A Structural Model of a Multitasking Salesforce


Appendix

A. Compensation Plan

Maintenance index of salesperson $j$ in period $t$ ($M_{jt}$) is a function of maintenance performance (i.e., the amount of repaid loans, relative to that of loans due in period $t$ ($R_{jt}/O_{jt}$)). Table A1 describes how the maintenance index depends on the share of loan amount in good standing in each period.

<table>
<thead>
<tr>
<th>% of loan amount in good standing</th>
<th>Index</th>
<th>% of loan amount in good standing</th>
<th>Index</th>
<th>% of loan amount in good standing</th>
<th>Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 87.5%</td>
<td>0</td>
<td>93 - 93.5%</td>
<td>0.75</td>
<td>96.5 - 97%</td>
<td>1.05</td>
</tr>
<tr>
<td>87.5 - 88.5%</td>
<td>0.5</td>
<td>93.5 - 94%</td>
<td>0.8</td>
<td>97 - 97.5%</td>
<td>1.08</td>
</tr>
<tr>
<td>88.5 - 90%</td>
<td>0.6</td>
<td>94 - 94.5%</td>
<td>0.85</td>
<td>97.5 - 98%</td>
<td>1.1</td>
</tr>
<tr>
<td>90 - 92.5%</td>
<td>0.65</td>
<td>94.5 - 96%</td>
<td>0.9</td>
<td>98 - 99%</td>
<td>1.15</td>
</tr>
<tr>
<td>92.5 - 93%</td>
<td>0.7</td>
<td>96 - 96.5%</td>
<td>1</td>
<td>99 - 99.5%</td>
<td>1.2</td>
</tr>
<tr>
<td>99.5 - 100%</td>
<td>1.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

B. Additional Results on Counterfactual Simulations

B.1. Counterfactual Simulation of An Alternative Incentive under Specialization Job Design

In this section, we consider an alternative incentive design under the specialization job allocation. In the main text, each salesperson is assigned to only one task and her bonus is based on the performance of the assigned task. An alternative incentive under the specialization scheme is an incentive contract where the hunter is evaluated based on both acquisition and maintenance performances. This incentive scheme could help solve the incentive misalignment issue of the specialization job design that we consider in the main text, where the issue is that the hunter does not care about future profitability of newly acquired loans.

We simulate specialized salespeople’s behaviors under the compensation plan that rewards hunters’ efforts to acquire good loans in Table A2. Following Table 5, we choose the incentive plan to be $Bonus = 0.5A$ for hunters and $Bonus = 0.75M$ for farmers, when specialized hunters are rewarded in terms of acquisition performance only. When hunters are incentivized based on both acquisition and maintenance performances, their incentive plan is chosen to be $Bonus = A \times M$, whereas farmers’ incentive plan remains as $Bonus = 0.75M$. Farmers are not evaluated in terms of hunters’ acquisition performances in any case because acquisition outcomes are realized prior to their maintenance effort and beyond farmers’ control at all.

Table A2 shows the acquisition and maintenance performance of good and bad loans; Net Present Value (NPV) of loans and incentive payout; and the firm’s profit under two incentive designs for specialized salespeople. We find that the profit increases by 33% if hunters’ incentive depend not only on acquisition performance but also maintenance performance. This happens because hunters now care about quality of acquired loans and hence do not acquire too many bad loans.

Although this incentive scheme seems more profitable, our interview with the firm tells us that it is not feasible to implement it. The firm’s main concern lies in the perceived unfairness across salespeople, because hunters would not accept that their bonus partly depend on farmers’ performances. For example, loan default
### Table A2 Profitability: Hunters incentivized on Acquisition only versus Hunters incentivized on Acquisition and Maintenance

<table>
<thead>
<tr>
<th>Hunters’ Incentive Design</th>
<th>Bonus = 0.5A</th>
<th>Bonus = A * M</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hunter</td>
<td>Farmer</td>
</tr>
<tr>
<td>Acquisition - Good</td>
<td>135.1</td>
<td>135.1</td>
</tr>
<tr>
<td>Acquisition - Bad</td>
<td>300.9</td>
<td>300.9</td>
</tr>
<tr>
<td>Maintenance - Good</td>
<td>95.9</td>
<td>95.9</td>
</tr>
<tr>
<td>Maintenance - Bad</td>
<td>111.3</td>
<td>111.3</td>
</tr>
<tr>
<td>Net Present Value (NPV)</td>
<td>372.7</td>
<td></td>
</tr>
<tr>
<td>Incentive Payout</td>
<td>80.4</td>
<td></td>
</tr>
<tr>
<td>Profit (NPV - Payout)</td>
<td>292.3</td>
<td></td>
</tr>
</tbody>
</table>

*1) Farmers’ incentive is Bonus = 0.75*M in both cases.  
2) Aggregate measures take account of share of hunters (68%) and that of farmers (32%) in the setting.  
3) All values are in 1,000 pesos.  
4) NPV is based on monthly interest rate of 1%.

is attributed not only to *ex ante* low quality of loans, which a hunter is responsible for, but also lack of maintenance effort by a farmer. Thus, a hunter cannot be penalized by loan defaults when he’s only in charge of loan acquisition. Furthermore, the random transfer policy is another obstacle to justify the incentive scheme. Right after transfers, farmers are not capable of collecting loans well. It is hard to convince hunters that their compensation partly depend on whether their new loans are maintained by transferred farmers or not. Despite the difficulty to implement the incentive scheme in practice, we believe the simulation sheds light on a way to address the incentive misalignment problem.

### B.2. Counterfactual Simulation of the Loan Repayment-based Incentive Plan under multitasking Job Design

As an alternative incentive under the multitasking job design, we consider the bonus based on repayment amount instead of the multiplicative incentive. Although our main results show that the multiplicative incentive help mitigate the incentive misalignment between the firm and salespeople, there is still a gap between the firm’s and salesperson’s incentives due to different performance metrics they are interested in. That is because the firm wants to maximize the total profit as a function of the *amount* of loan repayment, while the salesperson attempts to jointly maximize the amount of loan acquisition and the fraction of loan repayment. Thus, the bonus incentive based on the loan repayment amount would be of interest for the bank. Note that the loan amount based incentive is still a multi-dimensional incentive scheme as the bonus depends on both acquired amount and repayment probability.

To do so, we simulate a salesperson’s behavior under the compensation plan based on the amount of loan repayment. The incentive plan is chosen to be \( \text{Bonus} = \frac{\text{RepayAmt}}{(4 \times \text{Quota})} \), which normalizes total repayment amount by the acquisition quota for the average duration of loans (4 months) to compensate salespeople based on *repayment amount of loans per targeted acquisition amount*. Like other counterfactual simulations in Section 7, a salesperson is assumed to have private information about customers in every period, and is not affected by the transfer policy.
Table A3 compares the acquisition and maintenance performance of good and bad loans; Net Present Value (NPV) of loans and incentive payout; and the firm’s profit from two segments of salespeople under the two incentive plans. The profit considering Net Present Value of loans and incentive payout increases by 4% if the compensation scheme is changed to the repayment amount-based plan. Figure 9 visually represents the change in share of bad loans; repayment probability; and profit of each segment, which shows that if the two tasks are not separated in terms of performance metrics, a salesperson in the hunter segment is less likely to acquire bad loans by 8% (see Figure 9a), because of no incentive on the volume of acquisition, collect more loans by 13% (see Figure 9b) because of fewer bad loans and more effort in loan collection; and generate higher profit in the end (see Figure 9c). There is little difference in farmers’ performance between plans, which shows that farmers’ incentive is already aligned well with the firm’s incentive under the current compensation plan.

The implementation of the compensation plan based on loan repayment amount is, however, not straightforward in the actual setting due to the random transfer policy. Acquiring a new loan is not immediately incentivized at the time of loan origination, but is rewarded only when the loan is repaid later on. The gap in timing of performance and reward is problematic in this setting because a salesperson can be transferred right after loan acquisition, and before loan maintenance. Hence, the bank needs to jointly optimize the transfer policy together with the incentive plan, which is beyond the scope of the current paper.

### Table A3 Profitability: Current versus Repayment Amount-based Metrics

<table>
<thead>
<tr>
<th>Incentive Design</th>
<th>Current metrics ($Bonus = A \times M$)</th>
<th>Repayment amount-based metric ($Bonus = \frac{RepayAmt}{4 \times Quota}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hunter</td>
<td>Farmer</td>
</tr>
<tr>
<td>Acquisition - Good</td>
<td>93.1</td>
<td>98.3</td>
</tr>
<tr>
<td>Acquisition - Bad</td>
<td>196.8</td>
<td>102.9</td>
</tr>
<tr>
<td>Maintenance - Good</td>
<td>79.5</td>
<td>81.6</td>
</tr>
<tr>
<td>Maintenance - Bad</td>
<td>115.4</td>
<td>78.8</td>
</tr>
<tr>
<td>Net Present Value (NPV)</td>
<td>470.6</td>
<td>424.7</td>
</tr>
<tr>
<td>Incentive Payout</td>
<td>63.8</td>
<td>66.0</td>
</tr>
<tr>
<td>Profit (NPV - Payout)</td>
<td>406.8</td>
<td>358.7</td>
</tr>
</tbody>
</table>

1) Aggregate measures take account of share of hunters (68%) and that of farmers (32%) in the setting.
2) All values are in 1,000 pesos.
3) NPV is based on monthly interest rate of 1%. 
Online Appendix (Not for Publication)

Random Transfer

Our identification strategy takes advantage of the random transfer policy. This section verifies that the firm randomly chooses whether to transfer a salesperson. Table OA1, replicated from Kim et al. (2019), displays that transfer decision is not correlated with a salesperson’s acquisition or maintenance index in the previous period, tenure, or length of time since last transfer.\(^{35}\)

<table>
<thead>
<tr>
<th>Table OA1</th>
<th>Randomness of Transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td>DV: Transfer</td>
<td>(1)</td>
</tr>
<tr>
<td>Acquisition</td>
<td>-0.253</td>
</tr>
<tr>
<td>Index (t-1)</td>
<td>(0.274)</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0.00725</td>
</tr>
<tr>
<td>Index (t-1)</td>
<td>(0.474)</td>
</tr>
<tr>
<td>Tenure</td>
<td>0.000222</td>
</tr>
<tr>
<td>(0.00488)</td>
<td>(0.0151)</td>
</tr>
<tr>
<td>Time Since</td>
<td>-0.399</td>
</tr>
<tr>
<td>Last Transfer</td>
<td>(0.350)</td>
</tr>
<tr>
<td>(0.488)</td>
<td>(0.593)</td>
</tr>
<tr>
<td>Period FE</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>1637</td>
</tr>
<tr>
<td>Pseudo (R^2)</td>
<td>0.120</td>
</tr>
</tbody>
</table>

Variable Description for Loan Type Classification

Table OA2 lists the variables we put in the random forest model to estimate equation (OA2).

\(^{35}\)The exact values of the coefficients are slightly different from those reported in Kim et al. (2019). Our final sample here excludes salespeople whose aggregate acquisition or maintenance performance do not match with their bonus index (i.e. the case where some loans acquired and monitored by a salesperson are missing in the data), whereas our previous paper included such salespeople in the final data. Even though we observe only part of loans acquired or monitored by a salesperson, we could estimate how salesperson private information affects the profitability of each loan. Instead, this paper explores how salesperson private information affects aggregate performance of each salesperson.
Table OA2: Variables used to Develop a Predictive Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IRR</td>
<td>93,975</td>
<td>Mean (SD): 82.60 (25.35)</td>
</tr>
<tr>
<td>Acquisition Period</td>
<td>100,250</td>
<td>Top 2: Jul 2009 (22.8%), Oct 2009 (13.8%)</td>
</tr>
<tr>
<td>Loan Amt requested by Borrower</td>
<td>96,762</td>
<td>15343.7 (27743.6)</td>
</tr>
<tr>
<td>Whether Group Loan</td>
<td>87,973</td>
<td>Yes (2.4%)</td>
</tr>
<tr>
<td># of Co-signers</td>
<td>97.893</td>
<td>0.48 (0.58)</td>
</tr>
<tr>
<td>Whether Renewed Loan</td>
<td>100,250</td>
<td>Yes (31.01%)</td>
</tr>
<tr>
<td><strong>Loan/Borrower</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purpose of Loan</td>
<td>100,250</td>
<td>Top 2: Consumption (30.7%), Restructure (4.2%)</td>
</tr>
<tr>
<td>Borrower’s self-reported amt of loans</td>
<td>97,893</td>
<td>82486.4 (84906.6)</td>
</tr>
<tr>
<td>Borrower’s self-reported # of loans</td>
<td>97,893</td>
<td>5.18 (6.12)</td>
</tr>
<tr>
<td>Borrower Credit Rating</td>
<td>100,250</td>
<td>5 (70.6%), 4 (18.3%), 3 (5.2%)</td>
</tr>
<tr>
<td>Borrower Gender</td>
<td>84,065</td>
<td>Male (66.1%)</td>
</tr>
<tr>
<td>Whether Borrower owns Property</td>
<td>89,104</td>
<td>Yes (94.0%)</td>
</tr>
<tr>
<td>Borrower Occupation</td>
<td>100,250</td>
<td>Top 2: Grocery store (18.4%), Apparel store (11.9%)</td>
</tr>
<tr>
<td><strong>Loan Term</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Interest Rate (%)</td>
<td>100,250</td>
<td>7.28 (0.74)</td>
</tr>
<tr>
<td>Duration (months)</td>
<td>100,250</td>
<td>4.34 (3.98)</td>
</tr>
<tr>
<td>Amt (Pesos)</td>
<td>100,250</td>
<td>9,178.6 (72,238.2)</td>
</tr>
<tr>
<td><strong>Salesperson</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salesperson Level</td>
<td>98,845</td>
<td>Top 3: B (30.4%), C (24.4%), E (22.4%)</td>
</tr>
<tr>
<td>Salesperson Tenure (days)</td>
<td>98,845</td>
<td>1323.17 (772.48)</td>
</tr>
<tr>
<td>Branch</td>
<td>100,250</td>
<td>Top 3: 21 (2.8%), 22 (2.4%), 221 (2.4%)</td>
</tr>
<tr>
<td># Automatically processed loans</td>
<td>100,250</td>
<td>3.14 (3.07)</td>
</tr>
<tr>
<td># Visitors</td>
<td>100,250</td>
<td>5.56 (3.81)</td>
</tr>
<tr>
<td><strong>Compensation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whether Transferred</td>
<td>100,250</td>
<td>Yes (11.9%)</td>
</tr>
<tr>
<td>Acq. Index at Acq. Period</td>
<td>100,250</td>
<td>0.94 (0.43)</td>
</tr>
<tr>
<td>Acq. Quota at Acq. Period</td>
<td>100,250</td>
<td>551,351.5 (446,399.6)</td>
</tr>
<tr>
<td>Avg Maint. Index during Loan Cycle</td>
<td>100,250</td>
<td>0.88 (0.17)</td>
</tr>
<tr>
<td>Existing Loan Amt at Acq. Period</td>
<td>100,250</td>
<td>1,052,447 (775,657.3)</td>
</tr>
<tr>
<td>Loan Amt to Expire at Acq. Period</td>
<td>100,250</td>
<td>413,381.5 (315,223.9)</td>
</tr>
</tbody>
</table>

Forward-simulation Procedure

In this section, we explain the forward-simulation process in Step 2 of the estimation procedure, which estimates the value function from optimal policy estimates as follows:

1. Start from initial values of state variables $S_{j,0}$.

2. A random number $\alpha_{jt}$ is drawn from $U[0,1]$. If $\alpha_{jt}$ is smaller than 0.048, $j$ becomes a transferred salesperson in period $t$ ($t > 0$). Otherwise, $j$ is a continuing salesperson.

3. Compute optimal effort using estimated effort function at the first stage as $e_{kt}(S_{jt}; \hat{\gamma}_k)$ and the impact of exogenous shifters using estimated $\hat{\beta}_k$ at the first stage as $f(X_{jt}; \hat{\beta}_k)$ for each type of outcomes.
4. Unanticipated shocks for each performance $\epsilon_{jt}$ are drawn from a multivariate normal distribution of mean zero and estimated covariance $\hat{\Sigma}_k$.

5. Four performance outcome variables ($N_{jt}^G, N_{jt}^B, R_{jt}^G$ and $R_{jt}^B$) are realized.

6. State variables are updated based on the state transition estimates.

We repeat 1–6 for 14 periods for each of the 100 simulations. Note that the forward simulation includes the chance of transfers. We set the transfer probability to 0.048, which is the empirical likelihood of transfer during our observation window. The simulation enables us to estimate the value function from optimal actions for each segment given value of $\Theta_k$: $\hat{V}(S|k; \hat{e}_k, \hat{\beta}_k, \hat{\Sigma}_k, \phi, \Theta_k)$. Next, we do the same forward-simulation with deviated policy rule from the estimated effort function. The deviated effort policy parameters are denoted as $\tilde{e}_k$, where $\tilde{e}_k = e_k + \nu_k$. The perturbation from the effort under the optimal policy, $\nu_k$, is a draw from the normal distribution with mean zero and standard deviation 0.01. Then, we estimate the value function from deviated actions for each segment given structural parameters: $\tilde{V}(s|k; \tilde{e}_k, \hat{\beta}_k, \hat{\Sigma}_k, \phi, \Theta_k)$. The value function from deviated actions is no greater than the one from optimal actions by definition.

Other Estimation Results

Random Forest Results in Step 1a  Figure OA1 shows the importance of each variable in classifying the loans. Variable importance represents the normalized percentage of variance explained by each variable, a measure of how well out-of-bag predictions explain the target variance of the training set. We find that the interest rate, the time of acquisition, and the duration of the loan are the top three variables to predict ex-post IRR.

Quota Setting  This section reports the estimation results of the quota setting. Although we know that the acquisition quota for a continuing salesperson increase in response to the volume of her existing loans, the company does not reveal the exact function to set quota. Hence, we approximate it with the following transition function.

$$Q_{j,t+1} = 3 \sum_{l=0}^{3} \kappa_l \Lambda_l(O_{j,t+1}) \Lambda_l(Q_{jt}) + \mu_{t+1} + \epsilon_{j,t+1},$$

where $\Lambda_l(.)$ represents the $l^{th}$ basis of the $3^{rd}$ order Chebyshev polynomial, parameterized by $\kappa_l$. Period fixed effect $\mu_{t+1}$ is considered to capture the variability of quota depending on the market condition. The shock $\epsilon_{j,t+1}$ is not observed before the beginning of period $t + 1$. Table OA3 reports the estimation results for continuing salespeople in the first two columns and those for transferred salespeople in the third and fourth columns. The first two columns show that there is a positive relationship between the current quota and the next period quota for the continuing salespeople, while the last two columns show that there is no such a relationship for transferred salespeople as expected.

The positive relationship between $Q_{j,t}$ and $Q_{j,t+1}$ implies that there might be ratcheting incentive for salespeople. Although it does not affect our counterfactual analyses, it is interesting to quantify the effect of

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36 Similar to pseudo R-squared measure, the percentage of variance explained is computed as $1 - \frac{MSE}{VarY}$, where $MSE$ is mean squared error of out-of-bag predictions for each variable compared to the the outcome variable, and $VarY$ is variance of the outcome variable.
Kim, Sudhir and Uetake: A Structural Model of a Multitasking Salesforce

Figure OA1 Variable Importance

Table OA3 Transition of Acquisition Quota: Ratcheting Policy

<table>
<thead>
<tr>
<th></th>
<th>Continuing (1)</th>
<th>Continuing (2)</th>
<th>Transferred (1)</th>
<th>Transferred (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Lambda_1(O_{jt+1}) )</td>
<td>1.00*** 0.49***</td>
<td>1.29* 0.79</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.12) (0.75)</td>
<td>(0.94)</td>
<td></td>
</tr>
<tr>
<td>( \Lambda_2(O_{jt+1}) )</td>
<td>-0.001*** -1.30e-04 -0.002 -0.0009</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>( \Lambda_3(O_{jt+1}) )</td>
<td>6.9e-07*** -4.9e-08 -1.7e-06 5.02e-07</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.3e-07)</td>
<td>(2.3e-07) (2.4e-06)</td>
<td>(2.7e-06)</td>
<td></td>
</tr>
<tr>
<td>( \Lambda_1(Q_{jt}) )</td>
<td>-1.18*** -0.37*** -0.72 -0.10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.62)</td>
<td>(0.69)</td>
<td></td>
</tr>
<tr>
<td>( \Lambda_2(Q_{jt}) )</td>
<td>0.004*** 0.001*** 0.002 0.0007</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>( \Lambda_3(Q_{jt}) )</td>
<td>-2.3e-06*** -7.0e-07*** 1.6e-06 -9.9e-07</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.7e-07)</td>
<td>(2.6e-07) (1.5e-06)</td>
<td>(1.6e-06)</td>
<td></td>
</tr>
<tr>
<td>( \Lambda_2(O_{jt+1}) \times \Lambda_2(Q_{jt}) )</td>
<td>-2.0e-09*** -1.6e-09*** -1.60e-09 3.80e-10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.4e-10)</td>
<td>(3.1e-10) (2.6e-09)</td>
<td>(2.7e-09)</td>
<td></td>
</tr>
<tr>
<td>Period FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Intercept</td>
<td>16.68*** 17.68** 26.71 91.54</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.8)</td>
<td>(8.37) (25.73)</td>
<td>(55.83)</td>
<td></td>
</tr>
</tbody>
</table>

| N              | 2276          | 2276          | 154            | 154            |
|                | 0.28          | 0.45          | 0.23           | 0.31           |

salespeople ratcheting. In our context, the ratcheting incentive is not necessarily harmful for the company,
because salespeople engage less in adverse customer selection with ratcheting. It is an interesting future research question to ask.

<table>
<thead>
<tr>
<th>Table OA4</th>
<th>Distribution of Multidimensional Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Segment 1</td>
</tr>
<tr>
<td>( \text{Var}(\epsilon_{AG}) )</td>
<td>241.54</td>
</tr>
<tr>
<td>( \text{Var}(\epsilon_{AB}) )</td>
<td>329.71</td>
</tr>
<tr>
<td>( \text{Var}(\epsilon_{MG}) )</td>
<td>15.58</td>
</tr>
<tr>
<td>( \text{Var}(\epsilon_{MB}) )</td>
<td>39.79</td>
</tr>
<tr>
<td>( \text{Cov}(\epsilon_{AG}, \epsilon_{AB}) )</td>
<td>-116.09</td>
</tr>
<tr>
<td>( \text{Cov}(\epsilon_{AG}, \epsilon_{MG}) )</td>
<td>-0.81</td>
</tr>
<tr>
<td>( \text{Cov}(\epsilon_{AG}, \epsilon_{MB}) )</td>
<td>4.11</td>
</tr>
<tr>
<td>( \text{Cov}(\epsilon_{AB}, \epsilon_{MG}) )</td>
<td>-0.99</td>
</tr>
<tr>
<td>( \text{Cov}(\epsilon_{AB}, \epsilon_{MB}) )</td>
<td>16.89</td>
</tr>
<tr>
<td>( \text{Cov}(\epsilon_{MG}, \epsilon_{MB}) )</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Covariance Matrix of Shocks  
Table OA4 shows the estimated covariance of shocks (\( \Sigma_k \)) for each segment. Since multidimensional actions are jointly chosen, we allow for correlation between shocks within salesperson-period. Standard deviations in the parentheses are to be added. The distribution suggests that the unobserved acquisition shocks for good loans and bad loans (\( \epsilon_{AG}^k \) and \( \epsilon_{AB}^k \)) are negatively correlated. For example, if a natural disaster in a market switched the type of many potential customers from good to bad, a salesperson might acquire an unexpectedly low number of good loans but a large number of bad loans. However, the disaster might negatively affect existing customers’ repayment capability regardless of types (i.e., positive covariance of \( \epsilon_{MG}^k \) and \( \epsilon_{MB}^k \)).

Details on Specialized Salespeople’s Incentive Plan and multitasking Salespeople’s Additive Incentive Plan

To find the comparable incentive plan of specialized salespeople in the first counterfactual simulation (job task allocation), we need to find profit-maximizing multipliers on \( A(k^A) \) for hunters and \( M(k^M) \) for farmers. Under low \( k^A \) and \( k^M \), on one hand, the firm would incur lower cost than under high \( k^A \) and \( k^M \), because smaller incentives are paid out to the salespeople. On the other hand, hunters are less incentivized to bring in new loans and farmers are less motivated to collect past loans. Such trade-off between cost and benefit under different values of \( k^A \) and \( k^M \) makes it an empirical problem to find the profit-maximizing points of \( k^A \) and \( k^M \). We numerically solve for the profit-maximizing multipliers by grid search over \( k^A \) and \( k^M \). Figure OA2 compares firm profits (Net Present Value of loans - Incentive Payout to salespeople) when \( k^A \in \{0.25, 0.5, \ldots, 2.5\} \) and \( k^M \in \{0.25, 0.5, \ldots, 2.5\} \) and finds that \( k^A = 0.5 \) and \( k^M = 0.75 \) generate the highest profit from specialized salespeople. When farmers’ incentives are extremely low, e.g., \( k^M = 0.25 \), salespeople do not collect enough loans and end up generating negative profit. In Table 5, we compare profitability of multitasking versus specialized salespeople, when specialized salespeople are incentivized based on 0.75\( A \) (hunters) or 0.5\( M \) (farmers).

Similarly, the second counterfactual simulation to study incentive plan design requires us to find the additive incentive plan, i.e., \( \text{Bonus} = wA + (2 - w)M \), that is comparable to the current multiplicative plan.
In other words, we need to find profit-maximizing weight on Acquisition task relative to Maintenance task \((w)\) for salespeople under the additive plan. As \(w\) goes up, salespeople, hunters in particular, are likely to focus their effort on acquisition of new loans and not to collect enough loans to make profit for the company. This is equivalent to forcing all salespeople to specialize in acquisition in the extreme case, e.g., \(w = 0\). A very high \(w\), on the contrary, makes salespeople shirk prospecting for new customers. We do the grid search over \(w\) when \(w \in \{0.25, 0.5, ..., 1.75\}\) in Figure OA3 to compare the profit (Net Present Value of loans - Incentive Payout to salespeople) under different weights on \(A\) relative to \(M\). The exercise finds that \(w = 0.5\), which assigns higher weight on the maintenance task, generates the highest profit from the salespeople. A smaller \(w\) slightly hurts the firm’s profit because farmers do not exert enough effort to acquire new loans. Any bigger \(w\) than 0.5 motivates hunters to acquire unnecessarily many bad loans which are not collected in the end.

We report the detailed performance of each segment of salespeople, when salespeople are incentivized based on \(0.5A + 1.5M\) in Table 6 to compare profitability of multiplicative versus additive incentive plan.
Figure OA3 Grid Search to find Profit-Maximizing Additive Incentive Plan

\[ \text{Bonus} = wA + (2 - w)M \]